# In Search of Lost Peace: The Local Effects of Peacekeepers on Conflict Dynamics in Africa *


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**Abstract**

I examine the impact of UN peacekeeping interventions on short- and long-term conflict dynamics by constructing a high-resolution geo-coded dataset that combines peacekeeping deployment locations and conflict events. The event study results show that peacekeepers lead to a sustained reduction in the likelihood of conflict. However, conflict intensity—measured by conflict-related fatalities—escalates in the long run following the phased withdrawal of peacekeepers. Additionally, there is limited evidence that peacekeepers generate a "peace dividend" by revitalizing local economic activity, as indicated by nighttime light data. The limited long-term effectiveness highlights the challenges of international military intervention in conflict resolution. The contrasting findings on conflict likelihood and fatalities underscore the reactive nature of UN peacekeepers operating under the limited-use-of-force principle. A case study of UN peacekeeping operations in the Democratic Republic of the Congo in 2013 reveals that the offensive operation reduced fatalities. Finally, the lack of economic improvement further emphasizes the challenges of fostering recovery in post-conflict regions.



Keywords: Peacekeeping, Conflict Resolution, Event Study, Dynamic Treatment Effects

JEL Codes: C23, D74, F53



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# 1 Introduction

Conflicts impose devastating human and economic costs, particularly in Africa, where persistent intrastate conflicts result in widespread displacement and economic setbacks. While the costs of conflict are well-documented (Abadie & Gardeazabal, 2003; Hoeffler & Reynal-Querol, 2003), quantitative evaluations of peacebuilding policies remain scarce in the economic literature, with a few notable exceptions (Armand et al., 2020, 2023; Richard & Vanden Eynde, 2023; Sonin & Wright, 2022). In response to the conflicts, UN peacekeeping missions have been deployed across Africa to mitigate violence and facilitate recovery. Despite significant investments—over \$6 billion in annual funding and more than 70,000 personnel globally—their long-term effectiveness remains uncertain. While existing research highlights their short-term success in reducing conflict, their ability to prevent the resurgence of violence after withdrawal is understudied.

This paper evaluates the effectiveness of UN peacekeeping missions in Africa from 1994 to 2020, examining their impact on conflict onset (extensive margin), conflict-related fatalities (intensive margin), and local economic activity. A high-resolution geocoded dataset[1] is constructed by integrating UN peacekeeping locations (Cil et al., 2020), conflict data from UCDP (Sundberg & Melander, 2013), and nighttime light data to track economic trends (C. D. Elvidge et al., 2017). I also incorporate climatic shocks, including precipitation and temperature anomalies, which are recognized drivers of conflict (Burke et al., 2015).[2]

Leveraging a generalized difference-in-differences (DiD) approach, the analysis assesses both short- and long-term effects (de Chaisemartin & D'Haultfœuille, 2022). Event study results indicate that peacekeepers significantly deter conflict onset, as measured by the extensive margin. Their presence also reduces conflict intensity in the short term. However, peacekeepers show limited long-term impacts in reducing conflict-related fatalities, as violence often resurges after their withdrawal. Similarly, there is little evidence of sustained local economic recovery, as indicated by nighttime lights.

In addition to the continental analysis, I conduct a case study of UN Peacekeeping's offensive operations in the Democratic Republic of the Congo (DRC). This case study provides insights into whether stronger mandates enhance peacekeeping effectiveness. The findings suggest that offensive operations led to a significant reduction in non-civilian targeted violence but had limited success in protecting civilians or fostering sustained peace, reinforcing the broader challenges peacekeepers face.

The literature generally highlights the immediate benefits of deploying peacekeepers. For example, Hultman et al. (2013) and Fjelde et al. (2019) found a reduction in civilian deaths with

[1]The dataset employs a $0.5° \times 0.5°$ grid structure (approximately 55 km $\times$ 55 km at the equator), covering the African continent.

[2]I thank Joseph Gomes and Diego Malo Rico for sharing data on climatic controls and nighttime lights (Desmet et al., 2023; C. D. Elvidge et al., 2017).

increased peacekeeping presence. Likewise, Carnegie and Mikulaschek (2020) reported that additional peacekeepers led to fewer civilian deaths in the following month. Nevertheless, the long-term effectiveness of peacekeeping remains poorly understood, despite missions becoming increasingly multidimensional and frequently extended through new mandates.

This paper makes three key contributions to the literature. First, it provides a comprehensive evaluation of UN peacekeeping deployments in Africa from 1994 to 2020, offering one of the most extensive quantitative analyses of their impact on conflict dynamics. Unlike studies that focus on select cases of success or failure, this study spans a broad temporal and spatial scale, contextualized within the evolving international political landscape of the 1990s and twenty-first century. By examining the full spectrum of peacekeeping missions across Africa, the study provides a balanced and empirically robust assessment, avoiding selection bias in evaluating peacekeeping effectiveness.[3]

Second, this study introduces a novel distinction between the extensive and intensive margins of peacekeeping impacts, highlighting the nuanced challenges of implementing peacekeeping interventions. The findings reveal that while peacekeepers effectively reduce the likelihood of conflict occurrence (extensive margin), they face significant challenges in mitigating conflict intensity (intensive margin), especially in the long run. This distinction underscores the limitations of peacekeeping operations in addressing entrenched conflict dynamics while maintaining a reactive role responding to heightened violence. The case study of MONUSCO's 2013 offensive operations in the Democratic Republic of the Congo further supports this point by showing that offensive mandates can reduce non-civilian targeted violence but are insufficient to foster sustained peace.

Third, the study provides the first quantitative evidence that while peacekeepers contribute to short-term reductions in local violence, conflict intensity tends to escalate following their withdrawal, raising concerns about their long-term effectiveness. These findings suggest that peacekeeping missions, though successful in establishing temporary stability, may not address the deeper political and economic drivers of conflict, which resurface once external forces are removed. In addition to these contributions, the study underscores the economic implications of peacekeeping efforts, demonstrating limited evidence of a "peace dividend" in affected regions, as measured by nighttime light data.

The paper is organized as follows. Section 2 provides context on UN peacekeeping missions and the roles of peacekeepers. Section 3 outlines the conceptual framework guiding the hypotheses and analysis. Section 4 describes the data sources and presents summary statistics. Section 5 details the empirical strategy, while Section 6 reports the main findings. Section 7 tests the robustness of the results. Section 8 presents the case study. Finally, Section 9 concludes and suggests directions for future research.

[3] A complete list of missions covered in this paper, along with their respective starting years and durations, is provided in Table G.1 in the Appendix.

## 2 Background

This section briefly overviews the historical and political background of UN-led peacekeeping missions. Then, I discuss the operational framework of peacekeeping missions, focusing on how the "blue helmets" are deployed on the ground to carry out and execute their mandated tasks.

### 2.1 The United Nations and the History of Peacekeeping Missions

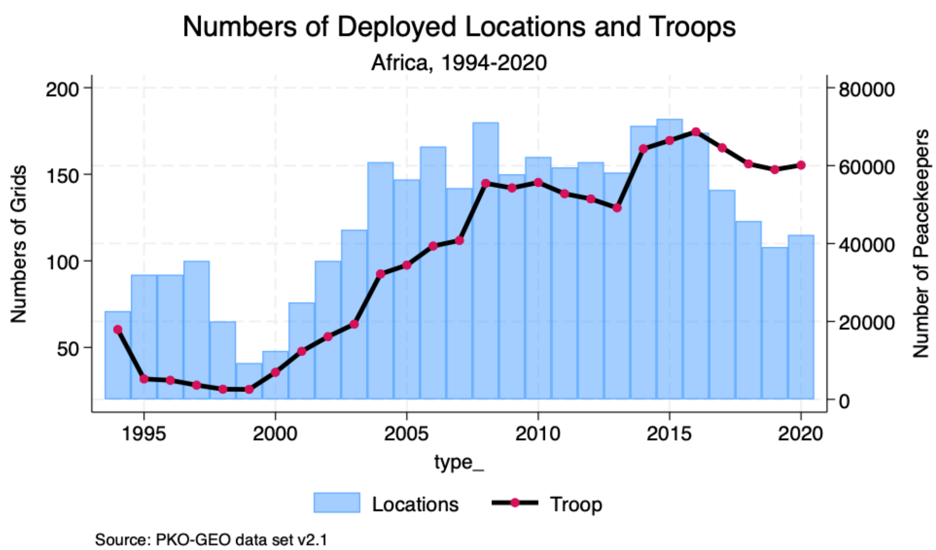



Figure 1: Numbers of Deployed Grids and Estimated Total Troops

UN peacekeeping began in 1948 during the Arab-Israeli conflict. After the Cold War, increased military capabilities among major powers enabled the UN to authorize more missions, peaking between 1988 and 1993 (Williams & Bellamy, 2021). This period shifted toward ambitious mandates, including humanitarian aid and state-building.

However, setbacks in Bosnia, Rwanda, Somalia, and Angola by 1995 fueled skepticism about UN-led missions, reducing deployments from over 70,000 peacekeepers in 1993 to fewer than 20,000 by 1996. Figure 1 shows this decline in Africa between 1994 and 2000. In response, the UN released the Brahimi Report in 2000, outlining several recommendations for improving peacekeeping operations and signaling a renewed commitment to peacekeeping.

Over the first two decades of the twenty-first century, most authorized missions have been in sub-Saharan Africa. The focus of this study is thus on Africa. This continent has hosted the most significant number of United Nations peacekeeping missions due to its unique challenges in armed conflict, political instability, and humanitarian crises. In 2020, there were twelve ongoing peacekeeping missions, with six located in Africa. These missions are characterized by multidimensional mandates featuring multidimensional mandates such as civilian protection, disarmament, and security training.

## 2.2 The Making of Peacekeeping Missions and Peacekeepers' Roles

*The Life-cycle of Peacekeeping Missions*

The life cycle of a peacekeeping mission can be divided into three interconnected phases: initiation and establishment, mandate execution, and transition leading to withdrawal. The process begins when the UN Security Council identifies a "threat to international peace and security." A draft resolution proposed by a member state or the Secretary-General must then be approved by the Security Council.

Following approval, the mission's mandate, scope, and duration are defined. The Department of Peace Operations (DPO) oversees planning, including technical field assessments, logistics, and deployment strategies. Member states pledge troops, police, and resources prepared for deployment. The UN then organizes transportation, supplies, and infrastructure to establish the mission on the ground. However, this process often takes around six months from resolution approval to full deployment ("Military Personnel", 2023).

During the execution of mandates, the mission regularly reports to the UN Security Council on its progress, challenges, and any changes in the situation. Adjustments may occur in response to evolving circumstances. In particular, specific missions required several years to reach their peak deployment capacity and witness shifts in mandates due to changing conditions on the ground. Finally, the peacekeepers' withdrawal may occur gradually, based on the security and political situation. Following the conclusion of a mission, the UN might maintain a residual presence, assuming more observational or supportive roles or transfer responsibilities to other entities.

United Nations peacekeeping missions pursue both immediate and long-term objectives. In the short term, they focus on minimizing casualties through interventions such as ceasefire monitoring, establishing safe zones for displaced populations, documenting human rights violations, and delivering humanitarian aid. These efforts also help create conditions for political dialogue among conflicting parties. In the long term, UN missions seek to restore and strengthen state authority by rebuilding governance structures and institutions weakened by conflict (Berdal & Sherman, 2023). The final stage of a UN mission is reflected in a phased withdrawal. Although withdrawal ideally reflects host-country stability, international politics, and funding constraints often influence decisions.

*The Peacekeepers' Roles and Activities*

Peacekeepers are expected to act based on the UN guidelines and principles, such as neutrality, impartiality, and the limited use of force (Tsagourias, 2006). However, implementing these principles on the ground often presents challenges that constrain peacekeepers' ability to act in certain situations. While they can use force in self-defense, these restrictions may limit their capacity to establish security, especially in active conflict zones (Di Salvatore et al., 2022). Maintaining neutrality in ethnically charged conflicts is particularly difficult, as peacekeepers strive to treat all parties impartially (Di Salvatore, 2020). Furthermore, engaging with local communities is essential for building trust, but public perception–often shaped by local media–can significantly influence cooperation and mission effectiveness (Di Salvatore, 2023).

Peacekeepers are also tasked to conduct a range of regular activities. In the security realm, peacekeepers conduct regular short-distance patrols to monitor security conditions and deter potential threats.[4] In areas with many displaced persons, peacekeepers establish and safeguard safe zones for vulnerable populations. They provide security escorts to facilitate humanitarian aid and support NGOs in ensuring safe passage. Observing and reporting human rights violations and vigilance in monitoring ceasefires are also part of the direct measures to prevent the resurgence of conflict (Ruggeri et al., 2017).

Finally, multidimensional peacekeeping missions aim to promote stabilization by supporting post-conflict reconstruction. Peacekeepers contribute to long-term stability through capacity building, training, and strengthening local security forces. They also play a vital role in monitoring and verifying disarmament processes to ensure compliance with peace agreements. During transitions from conflict to stabilization, peacekeepers often assist in organizing and overseeing democratic elections to enhance fairness and legitimacy, thereby preventing electoral violence—such as in the case of UNOCI in Ivory Coast.

# 3 Conceptual Framework

In this section, I present the conceptual framework that guides this study's empirical analysis, synthesizing results from the literature.

[4] The situation in Darfur, Sudan, is one example. The Darfur conflict has become a humanitarian crisis with outrageous violence against civilians since the early 2000s, with extensive displacement and human rights violations. Various mission reports cite that the short-range patrols are around 0 to 25 kilometers from the deployment bases (Halidu & Adeniji, 2018) On average, more than 200 patrols were conducted daily throughout Darfur, with many of these short-range patrols from deployment sites and around the internally displaced persons camps.

## 3.1 Short-term vs. Long-term Effectiveness

The effectiveness of peacekeeping missions can shift over time as intrastate conflict dynamics evolve. This framework differentiates between the short- and long-term impacts of peacekeeper deployments and explores the reasons for these differences.

*Short-term Effectiveness*

In the short term, peacekeepers are tasked with immediate conflict stabilization, focusing on protecting civilians, deterring violence, and monitoring ceasefires. Prior research highlights that the presence of peacekeepers can significantly reduce conflict events during deployment (Di Salvatore et al., 2022). However, short-term impacts are often driven by the presence effect–the direct role of peacekeepers as symbols of neutrality and deterrence.

For example, short-term effectiveness is evident in reduced civilian fatalities and the protection of internally displaced persons (IDP) camps, where peacekeepers serve as buffers between civilians and armed groups (Halidu & Adeniji, 2018). These immediate gains, however, often depend on the *continued presence* of peacekeepers in conflict-prone areas. Consequently, short-term successes remain vulnerable to sudden reversals, particularly when peacekeepers withdraw and are no longer available to maintain order (Di Salvatore, 2020).

*Long-term Effectiveness*

The long-term effectiveness of peacekeeping missions hinges on their ability to foster lasting peace and support post-conflict recovery. Over time, the presence of peacekeepers alone may prove insufficient to sustain peace, especially when underlying issues such as ethnic tensions, political instability, and economic stagnation persist (Di Salvatore, 2023). Recent critiques by Berdal and Sherman (2023) emphasize that UN mandates often fail to account for the complexities of local political economies, inadvertently perpetuating conflicts rather than resolving them.

Other mission mandates aimed at long-term effectiveness emphasize moving beyond immediate conflict deterrence to focus on capacity-building efforts, such as Security Sector Reform (SSR) and strengthening local institutions. Peacekeepers often assist in building security infrastructures—training national police and military forces, overseeing disarmament, demobilization, and reintegration (DDR) processes, and supporting democratic elections to establish legitimate governance. These largely technocratic activities are essential for strengthening state capacity and promoting sustainable peace, based on the assumption of a Weberian state (Berdal & Sherman, 2023). Yet, long-term outcomes remain mixed, sometimes resulting in premature peacekeeper withdrawals that leave security vacuums on the ground (Aloyo & Swenson, 2023).

Finally, as multidimensional peacekeeping missions grow more ambitious, their mandates often remain vague (Autesserre, 2019). The challenges of specifying and implementing these mandates can be understood through the lens of incomplete contracts (Hart & Moore, 1988). Hart and Moore (1988) argue that incomplete contracts can be revised as new information emerges, but communication limitations and the need for renegotiation constrain such revisions. In peacekeeping, these constraints highlight how Security Council decisions to revise mandates often struggle to achieve first-best outcomes, particularly when adapting to evolving conflict dynamics. Political bargaining within the Security Council further amplifies this ambiguity, as consensus among member states often results in compromises that lack operational clarity (Berdal & Sherman, 2023). These factors–including a limited understanding of local political economies that shape and sustain conflicts—suggest that long-term peacekeeping missions may struggle to achieve sustained stability, especially when mandates are vague and require frequent revisions to adapt to evolving conflict dynamics.

## 3.2 Extensive vs. Intensive Margin of Conflicts

In evaluating peacekeepers' effectiveness, it is crucial to distinguish between their impact on the extensive and intensive margins of conflict: (i) Extensive Margin–the probability of conflict occurrence or the likelihood that a conflict event will take place in a given area. (ii) Intensive Margin–the severity of the conflict, measured by the number of conflict-related fatalities.

*Extensive Margin*

Research suggests that peacekeeping forces can effectively lower the risk of conflict by deterring warring factions from engaging in violence in some instances (Hultman et al., 2013). Their presence *signals* international commitment to peace, raising the costs for actors considering violence. Much of this deterrence impact stems not only from the physical presence of peacekeepers but also from the broader political arrangements that accompany their deployment–such as ceasefire agreements, mediation efforts, and peace negotiations–which reinforce expectations of accountability and compliance. Furthermore, the UN's legitimacy as an impartial actor lends credibility to these efforts, amplifying the symbolic deterrent effects of peacekeepers, even in non-combat roles (Fortna & Martin, 2009; Salvatore & Ruggeri, 2017).

*Intensive Margin*

However, when it comes to reducing the intensity of conflict (i.e., fatalities), peacekeepers often face limitations. Research shows that while peacekeepers can be effective at preventing conflict *initiation*, they are less successful in mitigating casualties *once violence has begun* (Hultman et al., 2014). This difficulty can be attributed to several factors, such as restrictive mandates, limited military capacity, and rules of engagement that often prevent peacekeepers from taking more offensive actions or directly intervening in ongoing violence (Simpson, 2016). These challenges limit their ability to reduce the level of fatalities associated with active conflicts substantially.

Principal-agent problems could emerge because mandates–designed by the UN headquarters (principals)–often lack specificity and adaptability, forcing peacekeepers on the ground (agents) to make discretionary decisions under uncertainty (Grossman & Hart, 1983). This discretion can lead to moral hazard, where agents prioritize risk-averse strategies, such as avoiding confrontation, rather than actively intervening to prevent civilian fatalities (Simpson, 2016). The rules of engagement further constrain peacekeepers' ability to exert force, limiting their capacity to de-escalate ongoing violence. Additionally, misconduct cases (e.g., Beber et al. (2017)) underscore the principal-agent problem, as weak oversight mechanisms enable agents to act contrary to mission objectives without immediate accountability. These dynamics help explain why peacekeeping missions often succeed in deterring conflict onset but struggle to reduce conflict intensity once violence erupts.

In this study, I use state-of-the-art difference-in-differences econometric methods to assess peacekeepers' effectiveness across extensive and intensive margins and their short—and long-term impacts on conflicts. This dual perspective provides a comprehensive evaluation of peacekeeping missions, examining their ability to achieve immediate stabilization, reduce the scale and intensity of violence, and support sustained peace and post-conflict recovery.

# 4 Data and Descriptive Statistics

This section introduces the data sources and outlines variable construction. It then presents summary statistics from the constructed dataset used in the empirical analysis.

## 4.1 Data

This study draws on two primary data sources. The first is the Geo-PKO Dataset v.2.1 (Cil et al., 2020), which provides detailed information on the locations of UN peacekeepers deployed between 1994 and 2020. The second source is the UCDP Georeferenced Event Dataset v.22.1 (Sundberg & Melander, 2013), a geocoded and disaggregated dataset that records organized violence events.

*Geo-PKO Dataset v2.1*

The Geo-PKO Dataset provides fine-grained data on the geographical locations of peacekeeping deployments. Cil et al. (2020) digitized all deployment maps associated with UN peacekeeping operations from 1994 to 2020. These maps were sourced from reports drafted by mission chiefs and the UN Secretary-General, who regularly updated the UN Security Council on mission developments, including peacekeepers' current locations.[5] Each map was assigned a release date, including year and month information based on the associated reports. The frequency of map releases varies across missions, reflecting differences in the frequency of required updates.[6]

Constructing a monthly or quarterly panel dataset on peacekeeping deployments is challenging due to the irregular release of maps. One common assumption is that deployment status remains constant between map release dates, based on the expectation that the United Nations provides timely updates. However, this study avoids such assumptions and instead emphasizes long-term dynamics. Furthermore, Cil et al. (2020) noted that map update frequency often reflects the nature and complexity of missions. Consequently, this analysis focuses on year-to-year changes in conflicts and the impact of peacekeepers' presence within each year.

The primary data sources used in this study are mapped into a unified grid structure following the PRIO-GRID framework, which has a spatial resolution of $0.5° \times 0.5°$ (approximately 55 km$\times$55 km at the Equator) (Tollefsen et al., 2012). To address potential endogeneity issues arising from national borders influencing conflicts and mission deployments, grids intersecting multiple countries are subdivided into smaller sub-grids corresponding to each country (Desmet et al., 2023). Analyzing data at the grid-cell level helps mitigate endogeneity concerns related to correlations between local administrative boundaries and civil conflicts. The PRIO-GRID framework has been widely applied in conflict studies, including those by Berman and Couttenier (2015), Berman et al. (2017), and McGuirk and Burke (2020). In this study, a grid cell is classified as treated in a given year if at least one map records peacekeepers deployed within that cell. Peacekeeper presence is a binary variable, indicating treatment for the entire year regardless of specific monthly deployment details.

*UCDP Georeferenced Event Dataset v22.1*

The UCDP Georeferenced Event Dataset (UCDP-GED) documents organized violent events with geocoded details, including latitude and longitude. An event is defined as the use of armed force by an organized actor against another organized actor or civilians, resulting in at least one confirmed fatality. The dataset includes events with fatality estimates based on the best, lowest, or highest reported figures while excluding incidents with unclear or missing fatality data.[7] Unlike datasets that define conflicts based on a minimum threshold of 25 deaths per calendar year, UCDP-GED focuses on individual events, recording any incident of organized violence with at least one fatality (Sundberg & Melander, 2013).

The UCDP-GED dataset classifies conflicts into three categories: *state-based conflicts*, *non-*

[5] In addition to maps included in progress reports, the authors obtained supplementary maps from the UN Dag Hammarskjöld Library Cartographic Section upon request.

[6] Cil et al. (2020) noted that 17% of missions have one deployment map per year, while 46% have four or more maps (up to a maximum of eight) per year.

[7] This study uses the best estimates of fatalities for each recorded event.

*state-based conflicts*, and *one-sided violence*. State-based conflicts involve at least one armed actor affiliated with a state government. Non-state-based conflicts occur between two organized armed groups without affiliation to a state government. One-sided violence refers to the use of armed force by a state government or a formally organized group against civilians. Table F.1 in the Appendix provides a detailed description of these variables. This study also evaluates the effectiveness of peacekeeper deployments across these different types of conflicts.

Compared to other commonly used conflict datasets, such as the Armed Conflict Location and Event Dataset (ACLED), UCDP is better suited for analyzing peacekeeping interventions due to its event definitions. In contrast, ACLED includes lower-intensity incidents, such as protests, as well as remote violence, including incidents involving improvised explosive devices (ACLED, 2023). Since peacekeeping missions are less likely to address these types of violence, relying solely on ACLED data could lead to imprecise estimates.

Following the construction of the grid-cell-year panel data on peacekeeper deployments, geocoded conflict events are assigned to specific grids based on whether their coordinates fall within the spatial boundaries of each grid. Fatalities from each event are summed within each grid to create annual totals. I employ two definitions to capture the intensive and extensive measures of conflict. First, the intensive measure applies the inverse hyperbolic sine (IHS) transformation to the total fatalities within a grid each year. This transformation handles zero values while maintaining interpretability similar to a logarithmic scale. As a robustness check, Appendix Section C.2 tests alternative transformations (Chen & Roth, 2023). Second, the extensive measure is a binary variable indicating whether at least one conflict or violent event occurred within the grid during the year, capturing the presence or absence of conflict activity.

*Nighttime Lights and Control Variables*

This study also examines nighttime lights as a secondary outcome of interest. Nighttime luminosity is a proxy for economic activity, particularly in countries with limited data. Accurate calibration is necessary to ensure comparability over time by correcting for atmospheric interference and sensor inaccuracies (Wu et al., 2013).[8] To ensure consistency in a panel dataset, I use data from Desmet et al. (2023), covering the period up to 2019.

Finally, the control variables include rainfall and temperature shocks, identified as key predictors of conflict in the literature (Burke et al., 2015; Ciccone, 2011; Miguel et al., 2004). Following Desmet et al. (2023), these shocks are defined as standardized deviations from long-term average rainfall and temperature. Including these variables controls for their potential influence on conflict dynamics at the grid-cell level.

[8] Although harmonized nightlight data combining DMSP (1992–2013) and VIIRS (2012–2020) sources exist, measurement errors can persist (Weidmann & Schutte, 2017).

## 4.2 Descriptive Statistics

The African continent is divided into 12,431 unique grid cells. However, many of these cells did not experience fatal conflicts or peacekeeping activities during the study period. Consequently, 9,507 grid cells with neither fatal conflicts nor deployments are excluded from the analysis due to the fixed effects specified in panel data econometrics. This criterion leaves a final sample of 2,924 unique grid cells. Among these, 516 grids received peacekeeping interventions for at least one year between 1994 and 2020. Notably, 80 grids within the treated sample experienced multiple deployment-withdrawal episodes. The empirical strategy section further discusses how these repeated changes in treatment status influence the analysis.

*Summary and Comparisons of Outcome and PRIO-GRID Variables*

Table 1: Summary Statistics and T-test Mean Comparison

| **UCDP-GED** (1994-2020) | Never-treated | | Treated | | T-test | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | b | t |
| Pr(Any UCDP Event) | 0.061 | 0.239 | 0.190 | 0.392 | -0.128 | (-34.425) |
| Fatalities (Total) | 8.513 | 261.787 | 41.891 | 3141.216 | -33.378 | (-1.152) |
| Fatalities (State-based Conflict) | 4.628 | 239.011 | 2.096 | 30.299 | 2.532 | (2.589) |
| Fatalities (Non-state-based Conflict) | 1.277 | 18.795 | 0.463 | 9.084 | 0.814 | (7.297) |
| Fatalities (One-sided Violence) | 2.608 | 102.487 | 39.333 | 3138.989 | -36.724 | (-1.269) |
| N | 65016 | | 11772 | | 76788 | |
| **Nighttime Lights** (1994-2019) | Never-treated | | Treated | | T-test | |
| | mean | sd | mean | sd | b | t |
| Luminosity | 0.796 | 3.261 | 0.119 | 0.630 | 0.677 | (47.213) |
| N | 62530 | | 11258 | | 73788 | |

*Notes:* The table summarizes the outcome variables for the baseline sample, which excludes grids with multiple treatment status changes. The 2,924 effective unique grids exclude 80 grids with fluctuating treatment status, resulting in 436 treated observations out of 2,844 observations. Missing values in nighttime light data, caused by remote sensing quality, are not systematically correlated with treatment determinants but reflect variations in climate and cloud cover.

Table 1 indicate that, for the extensive margin, peacekeepers are deployed in grids with a higher likelihood of conflict. For the intensive margin, the average fatality difference between never-treated and treated grids is not statistically significant, primarily due to large standard deviations. However, treated grids exhibit significantly lower fatalities in state-based and non-state-based conflicts. The lack of a significant difference in one-sided violence stems largely from the extreme fatalities recorded during the 1994 Rwanda genocide. In addition to conflict outcomes, nighttime light data suggest that treated grids tend to have lower luminosity, indicating less human activity and potentially lower economic development in these areas.

To better understand the characteristics of grids where peacekeepers were deployed, I examine PRIO-GRID static variables from 1990 and 1994–before the study period–summarized in Table A.1 in the Appendix. The comparison shows that treated grids are, on average, farther from national capitals and have longer travel times to the nearest town. These findings align with theories on state capacity, suggesting that peacekeepers are often deployed in regions with weaker state influence and less developed public goods, such as road infrastructure (Braithwaite, 2010; Di Salvatore & Ruggeri, 2020; Hendrix, 2010; van der Lijn, 2009). Additionally, treated grids have about 4% less mountainous terrain, likely reflecting logistical challenges in deploying peacekeepers to rugged areas where air support is essential (Lacroix, 2020).

The data also show that treated grids are more likely to contain a higher concentration of historically excluded ethnic groups, based on 1990 ethnicity data from PRIO-GRID.[9] This pattern suggests that peacekeepers are deployed to regions with heightened ethnic tensions, aligning with the literature on ethnic conflicts (Esteban & Ray, 2008; Esteban et al., 2012; Montalvo & Reynal-Querol, 2005).

These descriptive statistics provide insights into the correlation between conflict and peacekeeper deployment patterns. However, caution is needed when interpreting them, as averaging data across grids and years may obscure dynamic effects, and static variables fail to capture the evolving nature of conflicts. In the following sections, I incorporate temporal aspects, such as deployment duration, and plot the yearly average conflict intensity to provide a clearer time-based perspective.

*Multiple Deployment Episodes and Duration of Deployment*

Of the 516 treated grids, 80 experienced multiple "flips" in treatment status, where peacekeepers were deployed, withdrawn, and redeployed. In contrast, the remaining treated grids underwent only one episode of treatment—either peacekeepers arrived and withdrew during the study period or remained deployed by its end. There is no statistically significant difference in overall fatalities between grids with multiple flips and those with continuous treatment (see Table A.2 in the Appendix). About 26.3% of the "flipped" grids experienced a one-year gap, with an average absence of 5.1 years.[10] Notably, 31.3% of these cases occurred in the Democratic Republic of Congo and 21.3% in Liberia, where multiple UN missions were deployed due to prolonged or recurring civil conflicts.[11]

[9] The original data come from the Geo-referencing Ethnic Power Relations dataset and are matched to the PRIO-GRID structure (Vogt et al., 2015).

[10] Figure A.1 in the Appendix illustrates the distribution of absence periods between consecutive deployments among flipped grids.

[11] For example, Liberia experienced a gap in peacekeeping, with UNOMIL operating from 1993 to 1997, followed by UNMIL from 2003 to 2018 after renewed conflict.

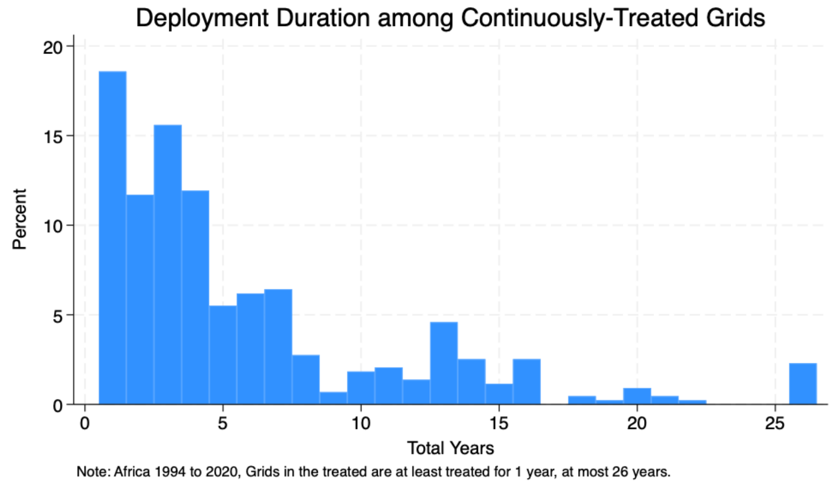



Figure 2: Distribution of Deployment Duration among Continuously-Treated Grids

Turning to grids without multiple treated episodes, the deployment duration among these grids varied, as shown in Figure 2. About 18.6% of them had peacekeepers' presence for only one year, and 63.3% experienced treatment for less than five years. The average deployment duration lasted 5.9 years, with longer durations in countries like Sudan, Liberia, Côte d'Ivoire, Sierra Leone, and the Democratic Republic of Congo, where prolonged conflicts were related to renewed and extended peacekeeping mandates.[12]

*Deployment and Conflict Intensity*

Figure 3 shows the average conflict intensity in treated and untreated grids over the study period.[13] The figure highlights notable spikes in conflict intensity, driven by events such as the Rwanda genocide in 1994 and the Ethiopia-Eritrea war between 1998 and 2000. These periods underscore heightened conflict and corresponding peacekeeping responses.

After 2005, treated grids showed an upward trend with fluctuations in conflict intensity, indicating that peacekeepers were often deployed to areas facing escalating and unstable violence. In contrast, untreated grids exhibit a more stable pattern. This temporal summary underscores the non-random allocation of peacekeepers, whose presence aligns with higher levels of violence over time.

[12] One exception is the UN Mission for the Referendum in Western Sahara (MINURSO), operational throughout the study period, primarily focusing on ceasefire monitoring and territorial disputes.

[13] To improve readability, the y-axis represents the average of inverse hyperbolic sine-transformed fatalities, reducing the impact of extreme values.

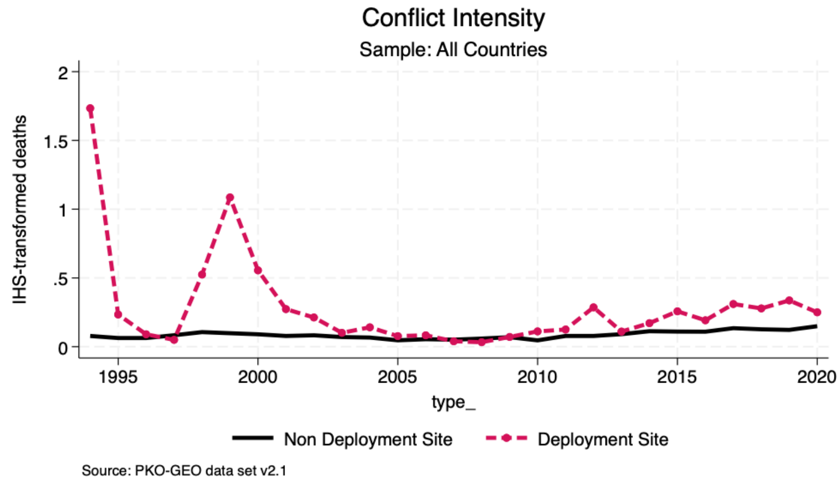



Figure 3: Evolution of Conflict Intensity between Treated and Not-Treated Grids

# 5 Empirical Framework

In the previous section, I summarized key features of the dataset and highlighted the non-random nature of peacekeeper deployments, including cases with multiple treatment periods. This section discusses these empirical challenges in detail and outlines the strategy used to identify the impact of peacekeepers' presence on conflicts.

## 5.1 Empirical Challenges

*Changes in Treatment Status*

Evaluating the long-term impacts of peacekeeper presence on conflict dynamics presents several empirical challenges. One such challenge arises from grids experiencing both deployments and subsequent withdrawals of peacekeepers, with some grids undergoing multiple changes in treatment status over time. To address this complexity, grids with multiple flips in treatment status are excluded from the primary analysis. However, these observations are incorporated in the robustness checks to provide a more comprehensive understanding.

The interpretation of treatment effects depends on the empirical strategy employed. The first approach applies a two-way fixed effects model, treating the initial arrival of peacekeepers as an absorbing treatment within an event study framework (Jacobson et al., 1993). This approach estimates the intention-to-treat (ITT) effect following the initial deployment.

Alternatively, recent advancements in difference-in-differences (DiD) methodology, as proposed by de Chaisemartin and D'Haultfœuille (2022), allow for the inclusion of changes in treatment status, including both the permanent and temporary withdrawal of peacekeepers. This study utilizes both approaches to evaluate whether accounting for peacekeeper departures influences the findings on long-term and post-mission conflict dynamics.

*Heterogeneity across Countries*

There are underlying differences across countries, such as which countries are more prone to civil conflicts and which are more likely to receive mission deployments, as well as mission-specific challenges from broader political macro trends. Therefore, it is crucial to account for country-specific differences (Berman et al., 2017; Desmet et al., 2023). In the empirical approach and main analysis, I incorporate country-year fixed effects into the standard two-way fixed effects model. The analysis focuses on the within-country, within-year variation in treatment effects by including country-year fixed effects instead of year fixed effects. Similarly, following the approach of de Chaisemartin and D'Haultfœuille (2022), the model can account for differential time trends in a non-parametric manner. For this purpose, I specify these differential time trends to vary across countries, allowing the model to capture country-specific temporal dynamics more accurately. Since deploying UN peacekeeping missions is often country-specific, this approach also helps account for differential effectiveness across countries.

## 5.2 Empirical Strategy

*High-Dimensional Fixed Effects Regression*

To establish a baseline event study benchmark, I adopt a high-dimensional fixed effects (HDFE) model (Correia, 2016). The high-dimensional fixed effects model incorporates grid fixed-effect and country-year fixed effects. The inclusion of fixed effects addresses several key factors. Firstly, grid-cell fixed effects control for time-invariant characteristics influencing peacekeeping deployment decisions, such as distance from the capital, accessibility to nearby towns, and historical ethnic composition, as shown in Table A.1. Secondly, country-year fixed effects capture potential changes in international politics that impact UN mission-specific contexts varying from country to country.

The baseline event study estimates the following regression,

$$
\begin{aligned}
Y_{it} = \alpha &+ \sum_{l=2}^{10} \beta_l^{lead} \text{Arrival}_i \times \mathbb{1}\{\text{lead}_t = \text{l}\} + \sum_{k=0}^{10} \beta_k^{lag} \text{Arrival}_i \times \mathbb{1}\{\text{lag}_t = \text{k}\} \\
&+ \mathbf{X}_{it}\Gamma + \mu_i + \delta\, \text{Country}_i \times \text{Year}_t + \varepsilon_{it}, \qquad (1)
\end{aligned}
$$

where $i$ represents the individual grid cell, and $t$ denotes the calendar year from 1994 to 2020. The dependent variable $Y_{it}$ can be specified in two ways: (i) a binary indicator for whether at least one conflict occurred in the grid cell during a given year (extensive margin) or (ii) a continuous measure of fatalities, transformed using the inverse hyperbolic sine (intensive margin). The grid fixed effect ($\mu_i$) captures time-invariant characteristics influencing deployment selection, while the country-year fixed effects absorb country-specific macro shocks and change international politics. The regression also includes time-varying control variables, $\mathbf{X}_{i,t}$, such as the standard deviations of yearly average rainfall and temperature, which can influence civil conflicts.

The coefficients of interest, $\beta^{lag}$, represent the dynamic treatment effect of deployment and quantify the impact of peacekeeping missions on conflict in the years following their arrival. These coefficients are compared against grids that did not experience peacekeeping deployment in the given year but still witnessed some conflict during the study period. The pre-treatment coefficients, $\beta^{lead}$, partially test the parallel trends assumption.[14] The coefficient one period before treatment $(t = -1)$ is normalized to zero.

*Issues of the Fixed Effects Model with Event Study Dynamics*

The fixed-effects model for estimating event study dynamics has certain limitations. First, it assumes treatment homogeneity, disregarding variations in effects over time and across observations. For instance, a grid hosting peacekeepers in 1995 and evaluated 10 years later is treated the same as a grid with a later deployment (e.g., 2000) but the same post-deployment evaluation period (e.g., 2010), despite differences in conflict evolution. This assumption can be overly restrictive, as peacekeepers' impacts are likely influenced by the timing of their deployment relative to international conflict trends. Moreover, the linear model may introduce bias by failing to account for treatment effect heterogeneity.

I incorporate recent advancements in the difference-in-differences (DiD) literature to address these limitations by adopting the $DID_\ell$ estimator proposed by de Chaisemartin and D'Haultfœuille (2022). This estimator provides a more flexible approach for estimating the effects of peacekeepers' presence, complementing the benchmark high-dimensional fixed-effects model.

*Heterogeneous Treatment Effects with Non-absorbing Treatment*

de Chaisemartin and D'Haultfœuille (2022) introduced the $DID_\ell$ estimator, a more flexible approach for evaluating dynamic treatment effects. The key idea is to compare a unit's actual outcomes (e.g., conflict-related indicators in a grid cell) after receiving treatment to a counterfactual scenario—what would have happened if the unit's treatment status had remained as it was in a previous period? This approach leverages groups that "switch" their treatment status between periods, either from untreated to treated or vice versa, to estimate the impact of these changes.

[14]The pre-event coefficients only serve as a partial test of parallel trends since the counterfactual outcomes cannot be directly observed, e.g., what would have occurred in the absence of peacekeepers (Kahn-Lang & Lang, 2020).

The $DID_\ell$ estimator aggregates these group and time-specific treatment effects into an event-study framework without imposing restrictions on treatment effect homogeneity. Additionally, this method accommodates non-absorbing treatments, allowing the analysis to capture the initial impact of peacekeeper deployments and the changes in conflict dynamics when peacekeepers withdraw or re-enter a given area.

## 5.3 Identifying Assumptions

*No Anticipatory Effect*

One key identifying assumption for estimating the causal impact of peacekeeper deployments on conflict is the absence of local anticipation of intervention. While peacekeepers are typically deployed to locations where the security situation is deteriorating, external factors such as logistical constraints, extreme violence, and bureaucratic delays also influence the timing and location of deployments.

To empirically test this assumption, I regress the level of conflict in period $t$ on a lead variable indicating treatment status in period $t+1$, controlling for grid and country-year fixed effects. A significant coefficient on the lead variable would suggest that conflict levels in the current period are associated with anticipated peacekeeper deployment in the next period. This could reflect either anticipatory behavior by local actors, such as strategic de-escalation or escalation of violence, or strategic positioning by peacekeeping operations, e.g., where areas with increasing conflict are prioritized for deployment.

By examining the direction and significance of this relationship, the analysis evaluates the plausibility of the no-anticipation assumption and provides insights into whether peacekeeper deployment decisions and local conflict dynamics are independent-a critical assumption for causal inference. As shown in Appendix Table A.3, peacekeepers are often deployed to areas with an increasing likelihood of conflict, suggesting that deployment decisions are reactive to rising risks. However, peacekeepers are less likely to be deployed to regions with extreme violence, likely reflecting operational constraints and logistical feasibility. While these findings are suggestive, they highlight the importance of accounting for potential biases when estimating the causal effects of peacekeeping interventions.

*Parallel Trends Assumption*

Although it is not possible to formally test the parallel trends assumption, visualizing potential violations through pre-trends in event studies can be highly informative. Furthermore, violations of the no-anticipation assumption are closely tied to possible violations of the parallel trends assumption. If unobserved characteristics influence both the likelihood of peacekeeper deployment and pre-existing conflict dynamics, such as the heightened risk of insurgency in treated locations observed one period before deployment, these same unobserved factors could lead to violations of parallel trends.

To address the potential concerns raised by violations of the no-anticipation and parallel trends assumptions, I employ the Honest DiD framework proposed by Rambachan and Roth (2023). This method extends the traditional difference-in-differences approach by formally accounting for possible violations of parallel trends and quantifying the sensitivity of estimates to alternative assumptions about the relationship between the determinants of treatment and potential outcomes over time.

By incorporating flexible assumptions about post-treatment dynamics and potential pre-trend violations, the Honest DiD framework offers a structured approach to bounding treatment effects under less restrictive assumptions. In the next section, I present the main results highlighting peacekeepers' impact on conflict dynamics. While the results provide key insights into the effects of peacekeeping interventions, the robustness checks in subsequent sections will further examine the sensitivity of these findings, including through the application of the Honest DiD method.

# 6 Results

## 6.1 Dynamic Two-way Fixed Effect

The baseline regression, as specified in Equation 2, produces the event study results illustrated in Figure 5 and Figure 6. These figures depict the estimated dynamics of peacekeeper deployment on conflict outcomes over time. For detailed tabulated results, including the exact magnitudes and standard errors of the estimates, refer to Appendix Table B.1, which provides estimates for $t = -2, 0, ..., 10$.

For the extensive margin, Figure 5 indicates that the likelihood of conflict was increasing prior to the arrival of peacekeepers. Following their deployment, however, there is a notable and consistent decline in the likelihood of conflict occurrence, with the effect gradually intensifying over time. The estimated coefficients for the post-treatment lags are statistically significant at the 1% or 5% level, starting at -0.1 in the immediate year of intervention (t = 0) and reaching -0.2 ten years after the initial deployment (t = 10). Given that the average likelihood of conflict occurrence in treated grids is 0.19 (with a standard deviation of 0.39), this reduction represents a relative decrease of 53% to 105% compared to the mean. Furthermore, these reductions correspond to 0.26-0.51 standard deviations, which is particularly meaningful given the high variability in conflict likelihood. These results highlight the substantial impact of peacekeepers' presence in reducing the probability of conflict in treated areas.

In contrast, the intensive margin results in Figure 6 show a lack of significant differences in conflict-related fatalities within-country and within-year when comparing locations with and without peacekeeper presence. In some periods, the presence of peacekeepers is even associated with a slightly higher number of fatalities. This finding aligns with the hypotheses outlined in the conceptual framework. While peacekeepers may have a signaling effect that deters potential conflicts, their limited capacity can constrain their ability to mitigate fatalities when conflicts do occur. This suggests that peacekeepers' effectiveness may be more pronounced in preventing conflict onset rather than reducing the intensity of violence once conflicts escalate.

*Diagnostics of Negative Weights and Heterogeneous Effects*

The Goodman-Bacon decomposition, summarized in Appendix Table B.3, reveals that no negative weights exist in the two-by-two comparisons underlying the dynamic TWFE estimates. Comparisons between the never-treated group and various timing groups with peacekeeping deployments primarily drive the coefficient.

While the absence of negative weights indicates no immediate issues with sign reversal, the potential for bias from heterogeneous treatment effects persists. Diagnostics in the Appendix further demonstrate that TWFE estimates may obscure meaningful variation in treatment effects across time and groups. To address these concerns, I compare the TWFE results with those obtained from the more robust $DID_\ell$ estimator proposed by de Chaisemartin and D'Haultfœuille (2022) in the next section.

## 6.2 Non-absorbing and Heterogeneous Treatment Effect

The estimations using de Chaisemartin and D'Haultfœuille (2022) account for heterogeneous treatment effects and non-absorbing treatments, including scenarios involving peacekeeper withdrawals. The resulting event studies for the extensive and intensive margins of conflict are presented in Figure 7 and Figure 8, respectively.

For the extensive margin in Figure 7, the conflict dynamic follows a similar pattern to that estimated with the high-dimensional fixed effects model–the likelihood of conflict occurrence increases before peacekeeper deployment and decreases afterward, with a comparable magnitude of the estimated coefficients.

In contrast, the intensive margin–measuring percentage changes in conflict-related fatalities–highlights a key difference between the two estimation methods, particularly at $t = 0$, when peacekeepers are deployed, and treatment is non-absorbing. The point estimate at $t = 0$ is now -0.146 (standard error = 0.099). By comparison, the absorbing treatment model yields an insignificant but positive estimate. This distinction is essential, as 18.6% of treated grids hosted peacekeepers for only one year (see Figure 2). The findings suggest peacekeepers may reduce conflict-related fatalities by approximately 14.6% during their first year.

As peacekeepers withdraw–often an endogenous decision influenced by conflict conditions–or missions remain deployed without sufficient capacity to address deep-rooted conflicts, their impact diminishes, as illustrated in the event studies with heterogeneous treatment effects and non-absorbing deployments. Furthermore, at time lags of eight to ten years post-deployment, the event studies reveal a significant increase in conflict-related fatalities, underscoring the long-term challenges of building peace through international peacekeeping missions.

*Heterogeneity Depending on the Types of Conflicts*

To better understand the escalation in conflict intensity observed in the long run (Figure 8), I examine the dynamics across different types of conflicts. The UCDP-GED classifies conflicts into three categories: state-based, non-state-based, and one-sided violence. State-based conflicts are the most prominent in the dataset, followed by one-sided violence and non-state-based conflicts. These categories account for approximately 47%, 22%, and 31% of total fatalities in the analyzed sample, respectively.

In Figures 9, 10, and 11, I present the event studies for state-based conflicts, non-state-based conflicts, and one-sided violence, focusing on the intensive margin and estimated using the method by de Chaisemartin and D'Haultfœuille (2022). Due to the low prevalence of non-state-based conflicts in the UCDP-GED dataset, the event study in Figure 10 does not yield statistically significant or interpretable results. In contrast, state-based conflicts show a clear escalation in conflict-related fatalities over time. The short-term reduction in deaths, however, appears to be primarily driven by one-sided violence during the immediate year of deployment, followed by potential escalation in later years.

The UN's ability to execute its mandate depends heavily on the host state's consent, without which intervention faces significant obstacles. Scholars have emphasized the importance of host state consent in shaping the implementation and effectiveness of peacekeeping missions (Duursma et al., 2023; Fortna, 2008; Johnstone, 2011; Piccolino & Karlsrud, 2011; Yuen, 2020). However, host state consent is not static; shifts in political dynamics can lead to the premature conclusion of peacekeeping missions, potentially leaving unresolved tensions. For instance, in June 2023, the UN ended its peacekeeping mission in Mali (MINUSMA) after the Malian government withdrew its consent, following heightened tensions linked to two recent military coups ("MINUSMA and protection of civilians", 2023).

Moreover, the dynamics of consent may extend beyond the state level. Rebel armed groups, for example, could interpret a host state's acceptance of international forces as a strategic threat, which might exacerbate their grievances and provoke further escalation unless accompanied by broader political solutions (Autesserre, 2010; Cunningham, 2010; Stedman, 1997). While this interpretation is speculative and requires further empirical investigation, it highlights how fragile the consent-based foundation of peacekeeping operations can be and how it may contribute to the observed escalation in conflict intensity over time.

### 6.3 Nighttime Lights

Finally, I also examine the evolution of nighttime lights, a proxy for economic and human activities, before and after the arrival of peacekeepers to evaluate their impact on local economic activity.

The effect of peacekeeper deployments on nighttime lights can be interpreted in two ways. First, deployments may increase nighttime luminosity due to military operations and logistical activities. Second, and more relevant to this study, peacekeepers may contribute to local stability and economic revitalization, creating a "peace dividend" (Rohner & Thoenig, 2021). While this study cannot fully disentangle these effects, the DiD estimators proposed by de Chaisemartin and D'Haultfœuille (2022) allow for a comprehensive analysis of the dynamic impacts of peacekeepers' arrival and departure. If peacekeepers effectively restore economic activity by ensuring stability, their impact should persist even after withdrawal. Thus, the econometric approach offers valuable insights into their long-term influence on local economies.

In Figure 12, I present an event study examining the impact of peacekeeper presence on changes in nighttime luminosity.[15] Prior to deployment, there were no significant differences between treated and untreated units, except in the year immediately preceding deployment, when treated grids exhibited slightly higher luminosity. In the first year of deployment, nighttime lights showed a marginal, yet statistically insignificant, increase.

However, following the phased withdrawal of peacekeepers, a significant decline in nighttime luminosity emerged. This decline, coupled with peacekeepers' limited success in reducing conflict-related fatalities, suggests that increased conflict intensity corresponds with decreased economic activity. These findings highlight the challenges of restoring local economic activities through peacekeeping interventions.

# 7 Robustness Checks

This section presents several robustness checks using alternative samples. First, I include grids that experienced multiple episodes of peacekeeping deployment to assess result stability. Second, I exclude grids from Northern African countries to evaluate the impact of regional differences. The robustness checks confirm that the main event study findings, particularly regarding conflict intensity, remain consistent across these alternative samples. Additionally, a leave-one-out analysis is performed to test robustness further. Together, these checks reinforce that the observed ineffectiveness of peacekeeper deployments in reducing fatalities is not driven by sample selection or specific country.

[15] The outcome variable, nighttime lights, is transformed using the inverse hyperbolic sine function to account for zero values in areas with no recorded nighttime lights.

### 7.1 Inclusion of the Grids with Multiple Deployments and Withdrawals

In the main analysis, 15.5% of the ever-treated grids were excluded to simplify interpretation and econometric specifications, as they experienced multiple deployments and withdrawals. However, this exclusion raises concerns that these areas may have distinct characteristics compared to those with a more consistent peacekeeper presence. To address this, a robustness check is conducted by including all grids that hosted peacekeepers, with gaps of no more than 10 years between consecutive deployments, effectively covering 98.8% of all treated grids. Figure 13 presents the results of this robustness check.

The expanded sample analysis reveals minimal differences in the significance of the estimated coefficients, with the overall conflict evolution pattern remaining consistent. However, at $t = 0$, the presence of peacekeepers is now associated with a statistically significant reduction in conflict-related fatalities at the 5% level (estimated coefficient $= -0.217$, standard error $= 0.105$). Additionally, a significantly lower conflict intensity is observed at $t = -1$, one year before peacekeeper deployment. Despite these changes in statistical significance, the overall results suggest a potential escalation in conflict intensity over the long run, particularly in areas where peacekeepers have phased out.

This robustness check reaffirms the primary findings, indicating that peacekeepers face challenges in reducing conflict intensity. The expanded analysis suggests that deployments are often to areas with previously lower conflict intensity, likely to minimize operational risks. As noted by Ruggeri et al. (2018), peacekeepers tend to arrive after a conflict has occurred and peaked, frequently positioning near major urban centers for strategic reasons.

### 7.2 Exclusion of the Grids in Northern African Countries

Peacekeepers have been deployed across diverse African countries with varying contexts.[16] Missions in Northern Africa, however, were less associated with intense civil wars and fatal conflicts, often serving in support or monitoring roles. For example, the United Nations Truce Supervision Organization (UNTSO) in Egypt and the United Nations Mission for the Referendum in Western Sahara (MINURSO) have had exceptionally long deployments, primarily focusing on political objectives rather than direct military interventions. To ensure the robustness of the results, I exclude Northern African countries from the sample, allowing for a focus on missions with stronger peacekeeping mandates in sub-Saharan Africa.[17] This restriction enables a more targeted analysis of peacekeeping missions directly addressing violent intrastate conflicts.

Figure 14 presents results replicating the analysis from Figure 8, excluding grids in North African countries. The findings reveal similar conflict intensity dynamics before and after the peacekeepers'

[16]The map in Section E in the Appendix shows peacekeeper deployment locations alongside areas with fatal conflicts.

[17]Tables G.1 in the Appendix provide an overview of all operations included in the primary analysis.

arrival. While the coefficient at $t = 0$ remains negative, the magnitude is much closer to null and no longer statistically significant, underscoring peacekeepers' additional challenges in sub-Saharan Africa. Furthermore, the escalation in conflict intensity at later periods persists. These results highlight the limited capacity of peacekeepers to address ongoing insurgencies and intrastate conflicts in sub-Saharan Africa.

### 7.3 Additional Robustness Checks

The Appendix presents additional robustness checks to address key concerns about the validity and robustness of the findings.

In Appendix C.1, the Honest Difference-in-Differences (Honest DiD) method (Rambachan & Roth, 2023) is applied to assess the potential violation of the parallel trends assumption, given the observed upward trend in conflict likelihood before peacekeeper intervention. Appendix C.2 explores the impact of alternative variable scalings and transformations on the results, addressing concerns related to the IHS transformation raised by Chen and Roth (2023). To evaluate sensitivity to specific countries, a leave-one-out analysis in Appendix C.3 ensures that the observed conflict dynamics are not driven by a single treated country. Lastly, Appendix C.4 corroborates the main results using the ACLED conflict event dataset, strengthening the robustness of the findings.

## 8 MONUSCO in Eastern DRC: A Case Study

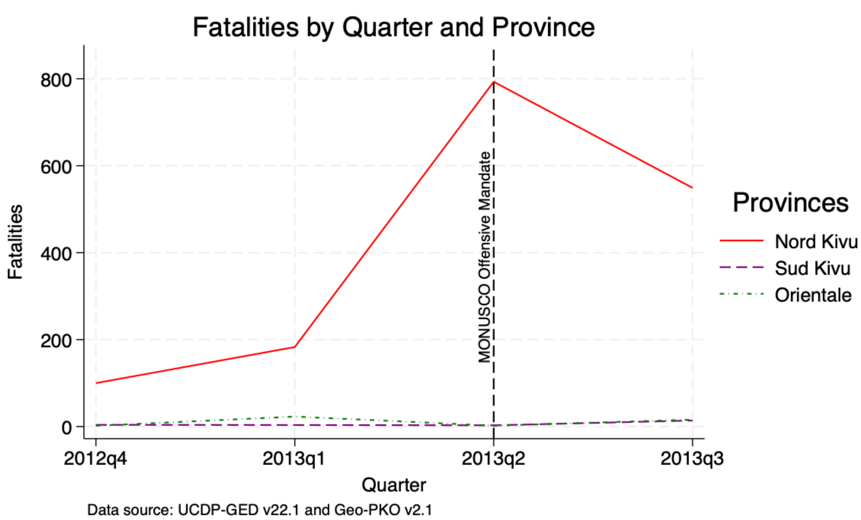



Figure 4: Conflict Trends Surrounding MONUSCO's Offensive Mandate

The conceptual framework highlights how the limited use of force principle constrains peacekeepers from actively intervening in ongoing conflicts, rendering their presence insufficient in preventing violence. The main results and robustness checks support this hypothesis.

In this section, I examine a case study in which MONUSCO peacekeepers were granted a specific task to "carry out targeted offensive operations... to prevent the expansion of all armed groups, neutralize these groups, and to disarm them."[18] This shift provides an opportunity to assess whether enhanced authorization to use force improves peacekeepers' effectiveness in mitigating heightened conflict intensity.

The transition to offensive operations occurred during a period when the M23 (Mouvement du 23 Mars) armed group was ravaging Eastern DRC. Although MONUSCO's core mandate remained unchanged, Resolution 2098, adopted in February 2013, authorized an "intervention brigade" tasked with combating armed groups. This brigade, fighting alongside the Forces Armées de la République Démocratique du Congo (FARDC), played a critical role in defeating M23. Additionally, in October 2013, 3,069 additional troops from South Africa, Tanzania, and Malawi were deployed, reinforcing existing peacekeeping bases in Eastern DRC, particularly in North Kivu province.

The offensive operation against M23 exceeded expectations, as MONUSCO had previously been regarded as a "toothless tiger" despite over a decade of engagement in the region (Vogel, 2014). Indeed, data compiled from the UCDP-GED and Geo-PKO datasets–consistent with the sources used in the main analyses–reveal a significant drop in overall fatalities in North Kivu province between Q2 2013 (April to June, when offensive operations commenced) and Q3 2013 (July to Septembe,r).

To examine the impact of offensive operations, I construct a grid-quarter panel dataset covering parts of the Orientale and Kivu provinces in Eastern DRC from Q4 2012 to Q3 2013.[19] Notably, the peacekeeper bases' locations remained unchanged during this period. The consistent locations showed that peacekeepers were not newly deployed to establish or expand military bases; instead, they operated under enhanced authorization to conduct offensive operations more effectively. Additionally, due to logistical constraints, the full deployment of additional troops was not achieved until the end of Q3 2013. This unique context allows the analysis to isolate the effect of the mandate change, focusing on the increased authorization to use force rather than the physical expansion of peacekeeping presence.

Following a similar empirical strategy as in the primary analysis, a grid cell is considered treated if peacekeepers were stationed there during the study period, with deployment patterns remaining

[18] MONUSCO takes the full name of the United Nations Organization Stabilization Mission in the DR Congo. Source: UN Security Council Resolution 2098 (2013). Additional background and case study details are provided in Appendix Section D.

[19] The grid size follows the main analysis, approximately 55km by 55km at the equator. A detailed map, including the current administrative boundaries of Haut-Uele, Ituri, Nord Kivu, and Sud Kivu, is provided in Figure D.1 in the Appendix.

Table 2: Estimated Effect of Mandate Change on Fatalities in Eastern DRC

| | (1)<br>IHS(Total Deaths) | (2)<br>IHS(Civilian-targeted) | (3)<br>IHS(Non-Civilian-targeted) |
|---|---|---|---|
| PKO×Post | -0.220<br>(0.121) | 0.225<br>(0.227) | -0.311<br>(0.167) |
| Cell FE | Yes | Yes | Yes |
| Province-Quarter FE | Yes | Yes | Yes |
| Observations | 520 | 520 | 520 |
| Adjusted R-squared | 0.714 | 0.432 | 0.731 |

*Notes:* This table presents the impact of peacekeeper presence on conflict intensity before and after MONUSCO's mandate shifted to offensive operations in Eastern DRC in 2013, using grid-quarter panel data. The sample consists of 130 grid cells observed over four quarters, with peacekeepers stationed in 11 to 13 grid cells per quarter. The deployment locations remained largely constant throughout the period. Civilian-targeted violence is defined according to the UCDP-GED dataset, where an event is classified as such if at least one party involved is civilians.

relatively stable in this case study. The post-treatment period is Q3 2013, when the authorized offensive operations and intervention brigade became fully operational. To control for potential confounders, the regression includes grid fixed effects to account for unobserved time-invariant characteristics and province-quarter fixed effects to capture shocks affecting the Orientale and Kivu provinces differently. This analysis aims to determine whether the observed decline in overall fatalities, as shown in Figure 4, can be attributed to the shift in peacekeepers' combat tactics during this period.

The results are presented in Table 2. Column (1) reports the impact on overall fatalities, column (2) focuses on fatalities from civilian-targeted violence, and column (3) examines fatalities unrelated to civilian-targeted events. The findings in column (1) suggest that the offensive mandate of peacekeepers was associated with a 22.0% reduction in total fatalities. Column (2) yields a positive but statistically insignificant estimate, indicating no clear evidence that the peacekeeping offensive mandate significantly impacted civilian-targeted violence. In contrast, column (3) suggests a 31.1% reduction in non-civilian targeted fatalities, highlighting that offensive operations were more effective in reducing armed confrontations not explicitly targeting civilians, such as clashes between armed groups or between rebels and security forces.

The effects observed in columns (1) and (3) are statistically significant at the 10% level (p ¡ 0.10). This limited significance may be attributed to the relatively small sample size, which restricts statistical power, and the potential influence of unaccounted time-varying factors. Additionally, using a 55 km by 55 km grid cell–while consistent with the primary analysis–may be too large to capture localized conflict dynamics within the confined geographical scope of Eastern DRC, potentially diluting the precision of the estimated effects.

Despite these limitations, the results provide important insights into the role of peacekeepers during this period. As Vogel (2014) summarized, the defeat of M23 was not solely due to the shift in peacekeepers' offensive strategy but also to several contributing factors, including the boosted morale of the Congolese national army, the loss of popular support for M23, and political factors such as the waning involvement of Uganda and Rwanda in supporting the armed group in 2013. Even when accounting for broader trends through province-quarter fixed effects, the findings suggest that areas with a peacekeeping presence experienced an overall lower level of conflict intensity following the change in combat tactics, effectively creating an "island of security" in the region, a strategy described by the MONUSCO (Vogel, 2014).

The limited effectiveness of MONUSCO in protecting civilians during this period, as shown in the results, must be understood within the broader context of Eastern DRC's long-standing conflict. The prolonged violence has contributed to a highly militarized society, making it challenging not only to identify and combat armed groups but also to distinguish between combatants and civilians. This complexity places MONUSCO's intervention brigade in a delicate position, where the imperative of civilian protection must be balanced with operational constraints (Vogel, 2014). Additionally, the shift to offensive operations increased risks for MONUSCO by placing UN personnel in direct combat roles, potentially exposing aid workers and civilians to retaliatory attacks from armed groups. This heightened exposure underscores the delicate balance between offensive mandates and the broader goal of civilian protection (Hunt, 2017; Müller, 2015).

In retrospect, the offensive approach adopted by UN peacekeepers and their military engagements had inherent limitations. The Intervention Brigade and MONUSCO's efforts did not bring a definitive end to the conflicts in Eastern DRC; M23 regrouped and resurfaced after 2017, while various other local armed groups continued their activities in the region. This case study of Eastern DRC aligns with the main findings, indicating that while UN peacekeeping operations can temporarily reduce conflict intensity under certain conditions, such as offensive mandates, their prolonged engagements and subsequent withdrawal often coincide with a resurgence of violence in previously deployed areas.

# 9 Conclusion

This study examines the impact of UN peacekeeping deployments on conflict dynamics across Africa, with a specific case study on the Democratic Republic of the Congo (DRC) to assess the effectiveness of offensive mandates. The findings indicate that while peacekeeping operations can temporarily reduce the likelihood of conflict, their long-term effectiveness remains uncertain, with conflict intensity often escalating after peacekeepers withdraw. These results highlight peacekeepers' persistent challenges in achieving sustainable peace, particularly in highly volatile environments. A critical distinction observed in this study is between the extensive and intensive margins of conflict.

Peacekeepers have proven more effective at reducing the probability of conflict occurrence (extensive margin). Still, they struggle to contain violence once it erupts, as reflected in the rising fatalities (intensive margin).

Further analysis reveals that a decline in one-sided violence primarily drives the short-term reduction in violence, whereas the long-term escalation in conflict intensity is primarily attributed to an increase in state-based conflicts. These findings indicate that while peacekeepers may temporarily deter non-state actors, they face more significant challenges in managing conflicts involving state forces and more complex political dynamics. The study also links increased conflict intensity to declining economic activity, as nighttime lights data indicates. The interconnected dynamics between escalating conflict intensity and reduced economic vitality highlight the difficulty of fostering economic recovery in post-conflict regions, reinforcing the need for comprehensive strategies that integrate security efforts with economic and social development.

This paper contributes to the literature by providing new empirical evidence on the dynamic effects of peacekeeping interventions across diverse African contexts. By incorporating a case study of MONUSCO's offensive mandate in the DRC, the study demonstrates that targeted military engagements may offer short-term conflict suppression but do not guarantee long-term stability. The case study underscores the importance of considering how variations in peacekeeping mandates—from traditional stabilization efforts to offensive operations—affect conflict outcomes.

As recent analyses emphasize, UN peacekeeping missions must engage with the political and economic landscapes they operate to maximize their effectiveness. A failure to address the underlying drivers of conflict—such as political exclusion, economic disparities, and governance challenges—can significantly limit the overall impact of peacekeeping efforts (Berdal & Sherman, 2023). This study reinforces that peacekeeping operations must move beyond a purely security-oriented approach and incorporate broader strategies that foster sustainable peace.

Future research should explore several important areas to deepen our understanding of peacekeeping effectiveness. First, incorporating expanded outcome variables—such as social cohesion, human development, and migration patterns—can provide a more comprehensive picture of peacekeeping's broader impact beyond conflict. Second, conducting comparative analyses across different regions with varying state capacity and political complexity levels will be crucial in understanding how political economy factors shape peacekeeping effectiveness. By comparing cases with distinct governance structures and economic conditions, future research can offer valuable insights into the conditions under which peacekeeping efforts are most likely to succeed.

While this study provides valuable insights, several limitations must be acknowledged. The reliance on grid-level data may not fully capture localized variations and spillover effects across regions. Additionally, the observational nature of the data necessitates more granular data and advanced identification strategies in future research.

In conclusion, this study contributes to a deeper understanding of UN peacekeeping operations' complexities in Africa. The findings emphasize that military engagement alone is insufficient to achieve long-term peace. Peacekeeping efforts must be integrated with political and economic strategies that address the root causes of conflict, ensuring a more sustainable and locally nuanced approach to peacebuilding. As international organizations face declining trust, reduced funding, and shifting global priorities (Walter et al., 2021), strengthening the alignment between peacekeeping efforts and sustainable development goals will be crucial in addressing modern security challenges.

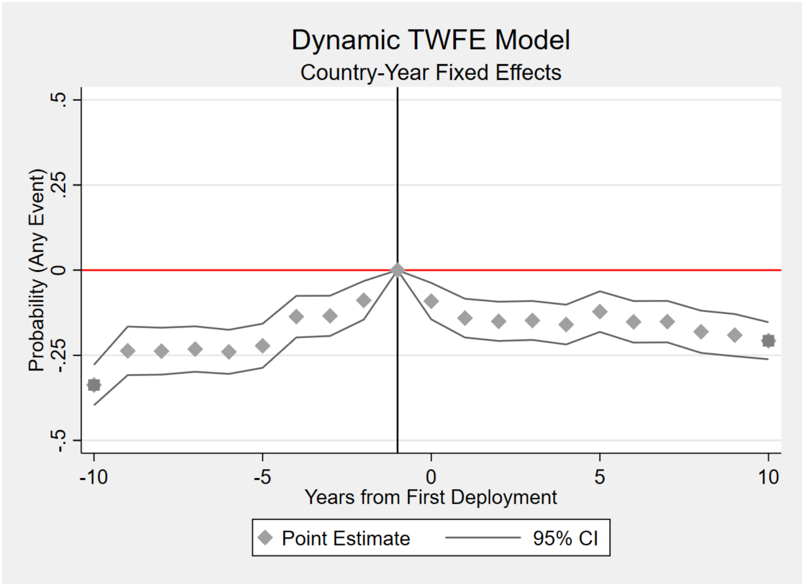



Figure 5: Event Study with Extensive Margin

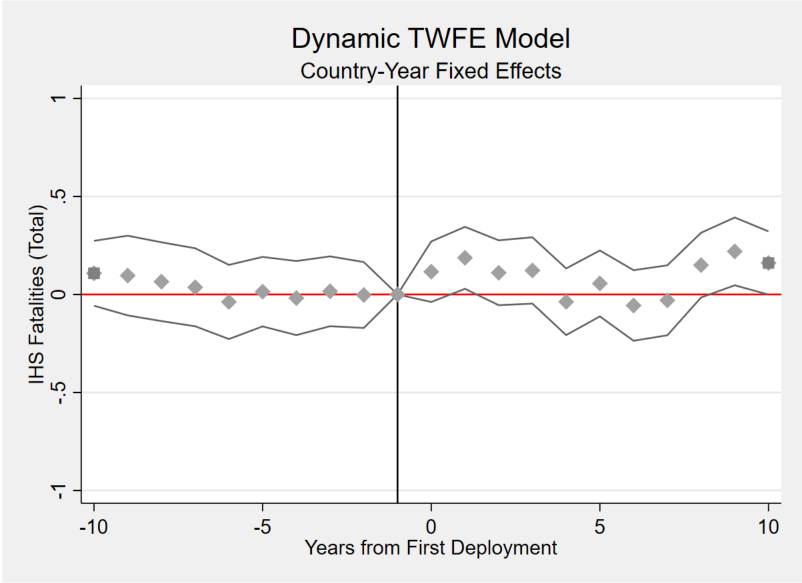



Figure 6: Event Study with Intensive Margin

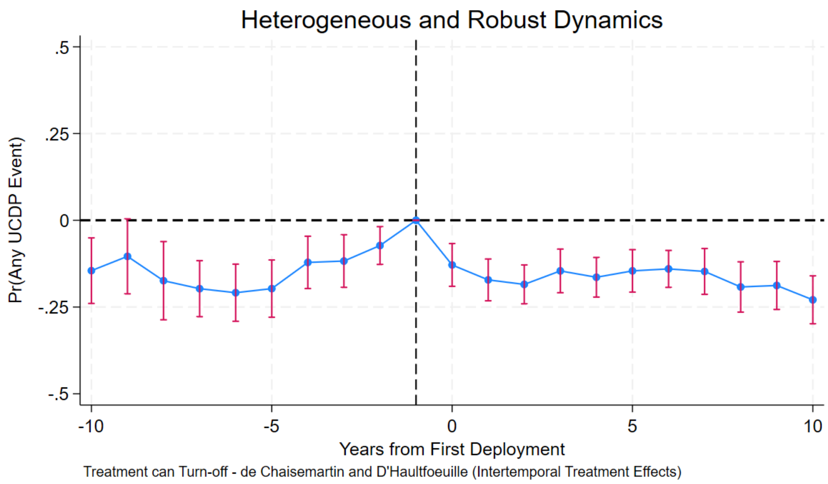



Figure 7: Robust Event Study with Extensive Margin

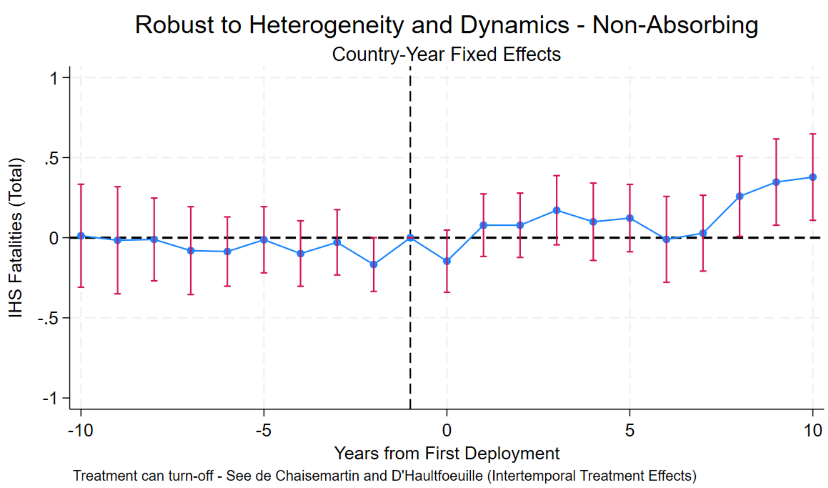



Figure 8: Robust Event Study with Intensive Margin

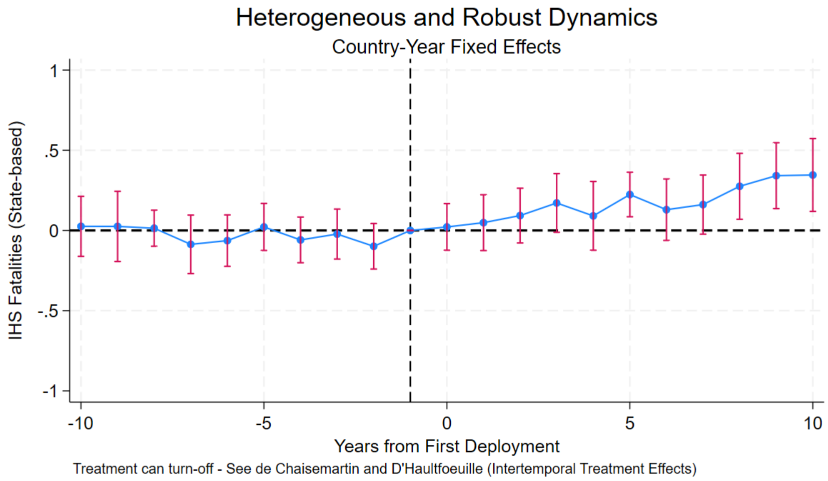



Figure 9: Fatalities Resulting From State-based Conflicts

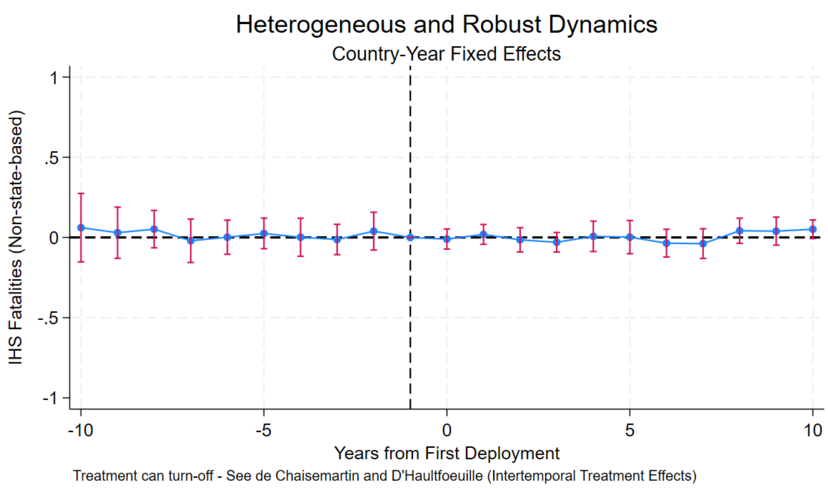



Figure 10: Fatalities Resulting From Non-state-based Conflicts

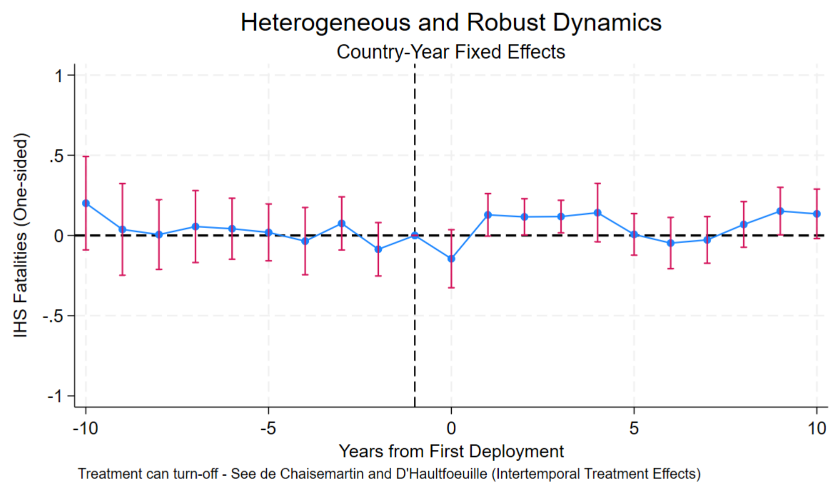



Figure 11: Fatalities Resulting From One-sided Violence

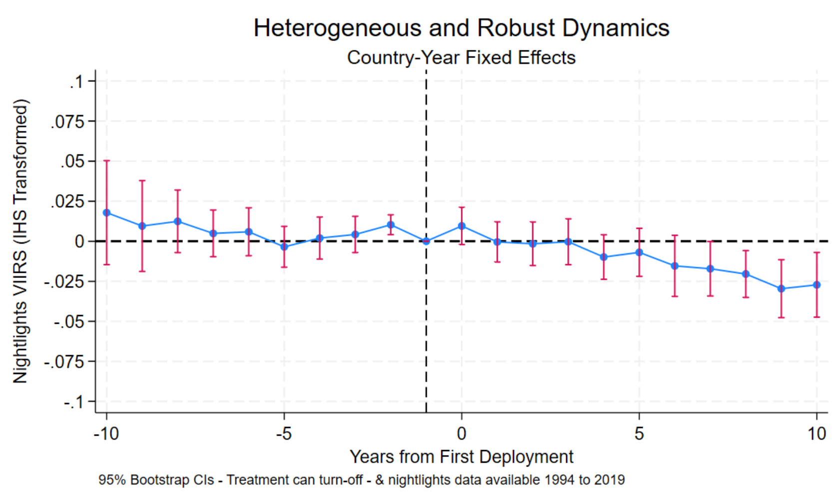



Figure 12: Event Study on Nighttime Lights (1994-2019)

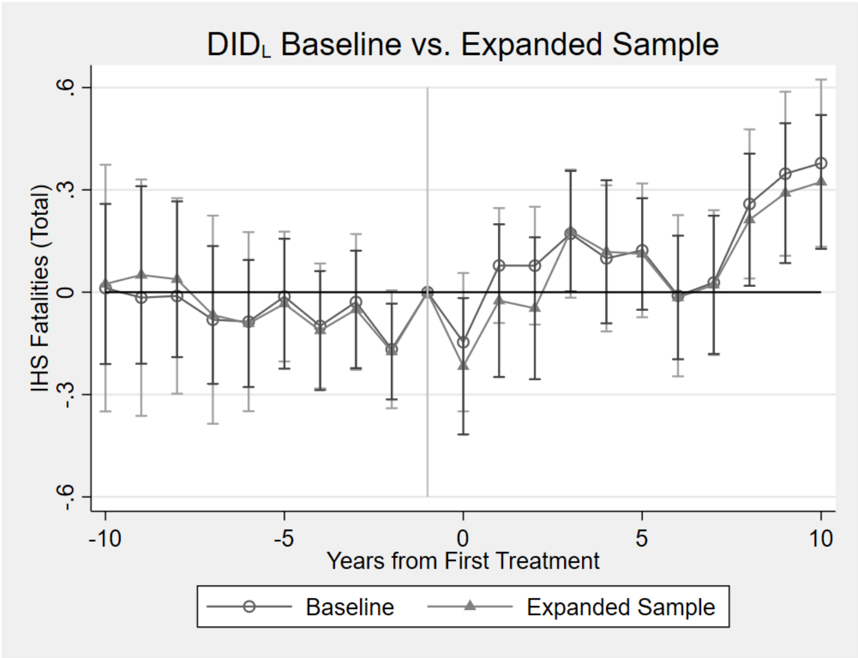



Figure 13: Comparing Baseline vs. Expanded Sample

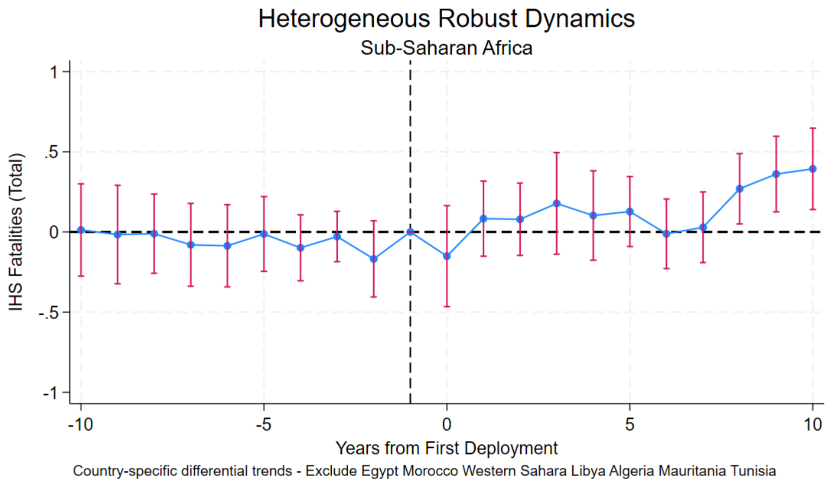



Figure 14: Sub-Saharan Countries Only

# Appendix A Additional Summary Statistics

## A.1 Time-invariant Variables

This table presents summary statistics to compare the time-invariant characteristics of treated and never-treated grids discussed in Section 4. While the fixed effects specification in panel econometrics controls for these differences, the table highlights systematic variations that may influence conflict dynamics and UN peacekeeper deployment decisions.

Table A.1: Summary Statistics and T-test Mean Comparison

| **PRIO-GRID Variables** (Snapshot of 1994) | Never-treated | | Treated | | T-test | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | b | t |
| Distance to Own Border (km) | 118.315 | 115.849 | 123.260 | 134.661 | -4.945 | (-0.720) |
| Distance to Capital$^{a}$ (km) | 587.014 | 413.625 | 633.383 | 430.933 | -46.369 | (-2.080) |
| N | 2408 | | 436 | | 2844 | |
| Mountainous Area (%) | 0.190 | 0.292 | 0.149 | 0.272 | 0.041 | (2.854) |
| N | 2397 | | 433 | | 2830 | |
| Time to the Nearest Town (Min.) | 442.329 | 370.786 | 542.926 | 472.265 | -100.597 | (-4.219) |
| N | 2408 | | 436 | | 2844 | |
| **PRIO-GRID Ethnicity** | Never-treated | | Treated | | T-test | |
| | mean | sd | mean | sd | b | t |
| # of Excluded Ethnic Groups 1990 | 0.806 | 0.729 | 0.918 | 0.723 | -0.112 | (-2.676) |
| N | 1928 | | 354 | | 2282 | |

*Notes:* This table presents summary statistics for time-invariant variables in the baseline sample, which excludes grids with multiple treatment status changes, consistent with Table 1. These variables provide insights into the characteristics of peacekeeper deployment locations and account for factors controlled using grid-cell fixed effects. *Sources:* PRIO-GRID (Tollefsen et al., 2015).

## A.2 Multiple Deployment Episodes

Figure A.1 shows the distribution of absence periods between consecutive deployments among flipped grids. Next, Table A.2 presents summary statistics on fatalities, comparing treated grids with and without multiple deployment episodes, as discussed in Section 4. Grids with multiple deployment episodes are described as experiencing multiple "flips" in treatment status. Overall, fatalities do not differ significantly between grids with and without multiple flips. However, fatalities from state-based conflicts are higher in grids without multiple flips, with the t-test comparison significant at the 10% level.

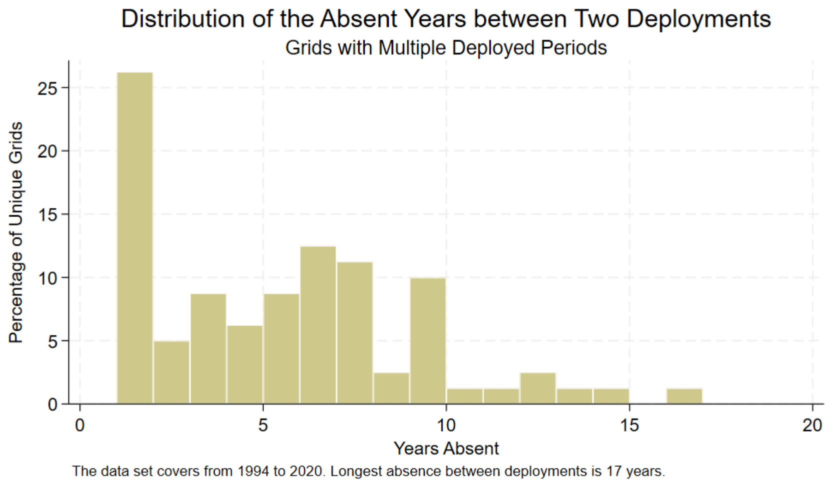



Figure A.1: Distribution of Absent Years among Grids Experienced Multiple Deployments/Arrivals

## A.3 No-Anticipatory Effect Assumption

Table A.3 examines the relationship between current conflict and future peacekeeper deployment to test the anticipatory effect assumption. The lead variable indicates whether a grid is treated in the subsequent period $(t+1)$. Results explore whether conflict levels in the current period are influenced by the anticipated arrival of peacekeepers, accounting for grid and country-year fixed effects.

The results in Table A.3 provide insights into the anticipatory effect of peacekeeper deployment and their relationship with conflict. Column (1) shows that the likelihood of conflict increases significantly in the period preceding peacekeeper deployment, suggesting that peacekeepers are often deployed reactively to areas experiencing escalating violence. However, Columns (2) and (3) reveal that the intensity of conflict, measured by fatalities, decreases slightly in areas scheduled for peacekeeper deployment. This suggests that while peacekeepers respond to rising conflict likelihood, they may avoid areas with extreme levels of violence, likely due to logistical challenges, life-threatening risks, or concerns about the feasibility of effective intervention.

While these results provide valuable insights into deployment patterns, they should not be interpreted as causal evidence of peacekeeping effectiveness. The results reflect correlations that help evaluate the plausibility of the no-anticipation assumption but are not conclusive about the causal impact of peacekeepers on conflict dynamics. Instead, they underscore the importance of understanding the complex interplay between conflict trends and deployment decisions.

Table A.2: Comparing Fatalities between Treated Grids with and without Flips in Treatment Status

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | b | t |
| Pr(Any UCDP Event) | 0.190 | 0.392 | 0.199 | 0.399 | -0.009 | (-0.953) |
| Fatalities (Total) | 41.891 | 3141.216 | 22.106 | 767.506 | 19.785 | (0.588) |
| Fatalities (State-based Conflict) | 2.096 | 30.299 | 0.919 | 10.712 | 1.177** | (3.198) |
| Fatalities (Non-state-based Conflict) | 0.463 | 9.084 | 0.332 | 7.702 | 0.130 | (0.680) |
| Fatalities (One-sided Violence) | 39.333 | 3138.989 | 20.854 | 767.273 | 18.478 | (0.549) |
| Observations | 11772 | | 1998 | | 13770 | |

*Notes:* Among the 516 treated grids, 80 experienced multiple deployment episodes, with 6 of these grids seeing peacekeepers leave for more than 10 years before returning. These six grids are excluded due to the prolonged absence. This sample of 510 unique grids is the treated group used in the robustness analysis in Section 7.

Table A.3: Testing the No-Anticipatory Effect Assumption

| | (1)<br>Pr(Any UCDP Event) | (2)<br>HS Fatalities(Total) | (3)<br>HS Fatalities(Total) |
|---|---|---|---|
| Lead | 0.137 | -0.080 | -0.074 |
| | (0.016) | (0.036) | (0.036) |
| Observations | 76680 | 76680 | 76275 |
| Grid-FE | Yes | Yes | Yes |
| Country-Year-FE | Yes | Yes | Yes |
| R-Squared | 0.371 | 0.314 | 0.311 |

*Notes:* Standard errors are clustered at the grid-cell level to account for within-grid serial correlation. Column (3) excludes Rwanda, as peacekeepers were deployed to multiple locations following the extreme violence of the genocide.

# Appendix B Additional DiD Results and Diagnostics

## B.1 Dynamic TWFE Model: Tabulated Result

The table above (Table B.1) presents the estimated coefficients from the dynamic two-way fixed effects regression specified in Equation (2) for interpretation and comparison. The impact of peacekeepers' presence on the intensive margin, measured by IHS-transformed fatalities and interpreted as percentage changes, is mostly statistically insignificant, except at $t = 1$ and $t = 9$, where the results suggest an increase in deaths. In contrast, the dynamics of conflict on the extensive margin, shown in column (2) of Table B.1, indicate that the likelihood of conflict increases before the arrival of peacekeepers and gradually declines following their deployment.

Table B.1: Estimated Event Study Coefficients in Figure 5

| | (1)<br>IHS Fatalities(Total) | (2)<br>Pr(Any UCDP Event) |
|---|---|---|
| lead2 | -0.003 | -0.089 |
| | (0.086) | (0.029) |
| lag0 | 0.116 | -0.091 |
| | (0.079) | (0.027) |
| lag1 | 0.187 | -0.141 |
| | (0.081) | (0.029) |
| lag2 | 0.111 | -0.150 |
| | (0.084) | (0.029) |
| lag3 | 0.122 | -0.148 |
| | (0.086) | (0.029) |
| lag4 | -0.037 | -0.160 |
| | (0.087) | (0.030) |
| lag5 | 0.056 | -0.122 |
| | (0.086) | (0.030) |
| lag6 | -0.056 | -0.152 |
| | (0.092) | (0.031) |
| lag7 | -0.030 | -0.151 |
| | (0.091) | (0.031) |
| lag8 | 0.150 | -0.181 |
| | (0.084) | (0.032) |
| lag9 | 0.220 | -0.191 |
| | (0.088) | (0.032) |
| lag10 | 0.160 | -0.207 |
| | (0.082) | (0.028) |
| Observations | 76680 | 76680 |
| Grid-FE | Yes | Yes |
| Country-Year-FE | Yes | Yes |
| R-Squared | 0.315 | 0.375 |

*Notes:* The lag coefficients are associated with $\beta_k^{lag}$ for $k = 0, 1, ..., 10$ and leads with $\beta_l^{lead}$ for $l = 2$ and the coefficient associated with lead1 (one period before treatment) normalized to zero. The sample includes 2,844 unique grid cells that experienced some conflict recorded in the UCDP-GED dataset and/or peacekeeper deployments during the study period (1994–2020). Of these, 436 grid cells were considered treated during the period. Additionally, 108 singleton observations were dropped due to the inclusion of fixed effects.

## B.2 Dynamic TWFE Model: Diagnostics

To address potential negative weighting issues that arise from multiple-group Difference-in-Differences (DiD) comparisons using a two-way fixed effects model, I employ the Goodman-Bacon Decomposition as a diagnostic tool (Goodman-Bacon, 2021). This approach examines whether negative weights are present, which could introduce bias in the event study setting.

Consider a basic two-way fixed effects (TWFE) model that includes only grid and year fixed effects, as opposed to the more demanding specification in Equation (2), which incorporates grid and country-year fixed effects. By limiting the fixed effects to grid and year, this diagnostic focuses on the canonical two-way fixed effects model, enabling me to interpret the estimated result as a weighted average of all possible two-group/two-period Difference-in-Differences (DiD) estimators in the data. This approach provides insight into whether negative weights pose a concern in the simplified setting, where country-year fixed effects are excluded and potential variations are retained. While this diagnostic does not fully account for the country-year fixed effects included in Equation (2), it serves as a valuable tool for understanding whether negative weights are likely to introduce bias in the more demanding specification with high-dimensional fixed effects.[20]

For the Goodman-Bacon decomposition, I first estimate the following regression specification:

$$Y_{it} = \alpha + \beta \text{Treated}_i \times \text{Post}_t + \mathbf{X}_{it}\Gamma + \mu_i + \delta_t + \varepsilon_{it}, \tag{2}$$

where $Y_{it}$ is the outcome of interest, which can either be a binary indicator for whether at least one conflict event occurred (extensive margin) or the IHS-transformed fatalities (intensive margin). The variable $\text{Treated}_i$ equals one if grid $i$ was ever treated (i.e., peacekeepers were present) and zero otherwise. $\text{Post}_t$ equals 1 for treated grids after the deployment of peacekeepers. $\mathbf{X}_{it}$ includes time-varying controls for precipitation and temperature shocks. Lastly, $\mu_i$ and $\delta_t$ denote grid-cell and year fixed effects, respectively.

Table B.2: Estimated Results Using a Basic Two-way Fixed-Effect Model

| | (1) IHS Fatalities(Total) | (2) Pr(Any UCDP Event) |
|---|---|---|
| Treat×Post | -0.220 | -0.030 |
| | (0.046) | (0.017) |
| Observations | 76788 | 76788 |
| Grid-FE | Yes | Yes |
| Year-FE | Yes | Yes |
| R-Squared | 0.011 | 0.015 |

The basic two-way fixed effects model yields different conclusions than the high-dimensional

[20] It is worth noting that this limitation arises from the current implementation of Goodman-Bacon's decomposition code, `bacondecomp,` which cannot be directly applied to demeaned treatment variable (which is not binary after demeaned calculations). Nevertheless, the results offer a meaningful diagnostic to support the main analysis.

fixed effects model. Specifically, the former suggests that peacekeepers are effective in decreasing fatalities. However, this difference arises because the basic two-way fixed effects model compares deployed and non-deployed locations within a specific year. In contrast, the high-dimensional fixed effects model, which includes country-year fixed effects, compares treated and non-treated locations within the same country and year.

Peacekeeping missions are deployed to consenting countries, influenced by factors such as peace agreements and political considerations. As a result, the basic two-way fixed effects model is more prone to selection bias, as the UN does not authorize peacekeeping missions randomly. Therefore, the results from the basic two-way fixed effects model should not be interpreted causally. Instead, they are presented here solely to facilitate the econometric application of the Goodman-Bacon decomposition.

Next, I investigate whether negative weights appear in the basic TWFE setting. In the sample, there are 27 timing groups (treated units that first received treatment during $t = 1994, 1995, ..., 2020$) and include an always-treated group and a never-treated group. The decomposition yields the following results:

Table B.3: Goodman-Bacon Decomposition Result

| | IHS Fatalities(Total) | | Pr(Any UCDP Event) | |
|---|---|---|---|---|
| | Total Weight | $\beta$ | Total Weight | $\beta$ |
| Timing_groups | 0.066 | -0.094 | 0.066 | 0.017 |
| Always_v_timing | 0.021 | 0.202 | 0.021 | 0.034 |
| Never_v_timing | 0.913 | -0.235 | 0.913 | -0.034 |
| Always_v_never | 0.000 | -71.572 | 0.000 | -22.999 |
| Within | 0.000 | -7.149 | 0.000 | -0.455 |

The Goodman-Bacon decomposition indicates that the majority of the estimated treatment effect ($\approx$ 91.3%) comes from comparisons between never-treated units and treated timing groups. This reduces concerns about negative weights often associated with within-timing group comparisons in staggered Difference-in-Differences settings. The never-treated group provides a stable counterfactual, mitigating the potential bias introduced by comparing early- and late-treated units. However, it is essential to note that systematic differences between treated and never treated units, such as baseline conflict intensity or regional stability, may still influence the results.

Additionally, the substantial coefficients are associated with negligible weights, indicating that the comparison between always-treated versus never-treated contributes minimally to the overall estimate. These coefficients likely reflect idiosyncratic effects within minimal subgroups and should not be over-interpreted.[21]

[21]For always treated units, the treatment status does not change over time, leading to minor to no within-unit

In conclusion, the basic two-way fixed effects model and the decomposition exercise provide insights into potential biases that could arise in the high-dimensional fixed effects model with country-year fixed effects. The Goodman-Bacon decomposition shows that concerns about negative weights are not present, indicating that the various comparisons across groups in the staggered treatment setting are less affected by this source of bias, thereby supporting the robustness of the results.

Similarly, using the basic two-way fixed effects model and following the diagnostic measure proposed by de Chaisemartin and D'Haultfœuille (2020), I assess whether the TWFE coefficient is consistent with a data-generating process (DGP) where the local average treatment effects (LATEs) have a mean of zero and a standard deviation of $x$, a potential source of bias. This approach assumes that the fixed-effects regression satisfies the assumption of common trends and that the treatment effects of the groups do not change over time. A low value of $x$ indicates that even small treatment effect heterogeneity could significantly bias TWFE estimates. The diagnostic measure should be compared with the dynamic TWFE coefficients to assess whether the observed $x$ reflects substantial or negligible heterogeneity.[22]

For the intensive margin, the diagnostic measure yields $x = 0.341$, representing the standard deviation of the potential treatment effect (i.e., heterogeneity). At $t = 0$, the coefficient estimated by the basic TWFE model is $-0.220$ (with a standard error of 0.046), which is statistically significant. Assuming that treatment effects are drawn from a normal distribution with a mean of zero and a standard deviation of $x$, the 95% confidence interval for the range of treatment effects (LATEs) is $[-1.96x, 1.96x]$, or approximately $[-0.668, 0.668]$.

Given that $|-0.220|$ lies well within this range, the observed treatment effect is consistent with the degree of heterogeneity implied by $x$. Moreover, since $|-0.220|$ represents the plausible estimate of the treatment effect at $t = 0$ under standard two-way fixed effects assumptions, it can also serve as a reasonable proxy. This further supports the conclusion that the diagnostic measure $x$ reflects substantial yet plausible treatment effect heterogeneity. These findings align with concerns raised in the literature that TWFE models may obscure heterogeneity when treatment effects vary across groups and periods (de Chaisemartin et al., 2019).

For the extensive margin, the diagnostic measure yields $x = 0.117$. At $t = 0$, the basic TWFE model coefficient is $-0.03$ (standard error $= 0.017$), which is significant.[23] These results underscore

variation. As a result, these comparisons rely on differences between these units and the never-treated group, which may exhibit vastly different conflict dynamics. Countries like Rwanda (always treated) experienced uniquely high fatalities due to its distinct historical circumstances. This makes the treatment effects incomparable to those of other groups.

[22] The command is `twowayfeweights`. See de Chaisemartin and D'Haultfœuille (2020).

[23] Assuming treatment effects follow a normal distribution with mean zero and standard deviation $x$, 95% of effects fall within $[-1.96x, 1.96x]$, or approximately $[-0.229, 0.229]$. Since $|-0.128| < 0.229$, this suggests that $x$ reflects substantial treatment effect heterogeneity.

the importance of accounting for treatment heterogeneity in the intensive and extensive margins of conflict outcomes. Together, these diagnostics highlight the limitations of the basic two-way fixed effects model in capturing dynamic and heterogeneous treatment effects.

# Appendix C Additional Robustness Checks

## C.1 Parallel Trends Assumption: Honest DiD

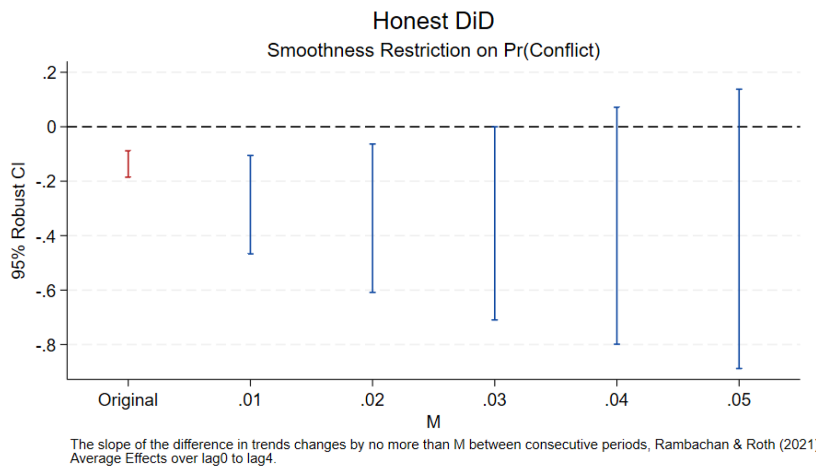



Figure C.1: Robustness of Average Short-term Effect

The event study results in Figure 5 reveal a clear pre-treatment trend in the likelihood of conflict events. Specifically, the probability of any conflict event exhibits a linear and upward trajectory in the years leading up to the first deployment of peacekeepers (from $t = -10$ to $t = -1$). This trend suggests that treated units were already experiencing an increasing likelihood of conflict before the intervention, which raises concerns about the validity of the parallel trends assumption underlying standard Difference-in-Differences (DiD) estimates.

To address this issue, I apply the Honest DiD framework (Rambachan & Roth, 2023), which allows for a slight and smooth divergence in pre-treatment trends in the likelihood of conflicts between treated and never-treated units. Specifically, I impose smoothness restrictions using a set of small values for the parameter $M$ (e.g., $M = 0.01, 0.02, ..., 0.05$), which constrain the maximum allowable pre-trend deviation to a modest range of $\pm 1\%$ to $\pm 5\%$ regarding the likelihood. The choice of a small $M$ is also justified by the linear and gradual upward nature of the pre-treatment trend observed in the main result. By allowing for this limited deviation, the Honest DiD framework tests whether the post-treatment decline in the probability of conflict remains robust once the observed

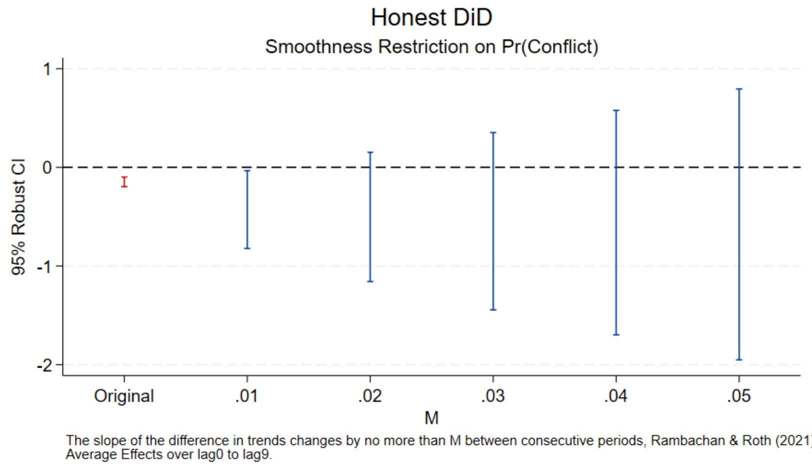



Figure C.2: Robustness of Average Long-term Effect

pre-trend is considered.

I apply the Honest DiD framework with smoothness restrictions for shorter-term effects (averaged over $t = 0$ to $t = 4$) and long-term effects (averaged over $t = 0$ to $t = 9$). The short-term average effect (Figure C.1) remains statistically significant under modest deviations in pre-trends (e.g., $M = 0.01, 0.02, 0.03$). However, when considering longer-term effects (Figure C.2), stricter smoothness restrictions (i.e., smaller $M$) are required to maintain statistical significance. This reflects the fact that when allowing for greater trend deviations, the long-term averaged effect is more sensitive to assumptions about pre-treatment parallel trends.

## C.2 Robustness to Alternative Scales of the Dependent Variable

In line with recent developments in the econometric literature highlighting the limitations of the inverse hyperbolic sine (IHS) transformation (Chen & Roth, 2023), this section conducts a robustness exercise to test how different levels of transformation of fatalities affect the observed conflict dynamics.

First, I present summary statistics for IHS-transformed fatalities using the original values from the UCDP dataset, scaled by a factor of ten and scaled down by dividing by ten. Table C.1 shows that the up-scaled transformed variable has the highest mean and standard deviation, the original scale lies in the middle, and the down-scaled transformed variable has the lowest mean and standard deviation. These patterns are consistent with the properties of the IHS transformation.[24] Next, I

[24]The IHS transformation compresses large values less aggressively than a logarithmic transformation, retaining more of their original scale. Consequently, scaling amplifies or compresses the influence of large outliers, leading to

| | N | mean | sd | min | max |
|---|---|---|---|---|---|
| IHS(fatalities) | 76788 | 0.376 | 1.172 | 0 | 13.393 |
| IHS(fatalities×10) | 76788 | 0.643 | 1.853 | 0 | 15.696 |
| IHS(fatalities÷10) | 76788 | 0.156 | 0.600 | 0 | 11.091 |

Table C.1: Summary Statistics of IHS-Transformed Fatalities with Different Scales

present the event study results estimated using de Chaisemartin and D'Haultfœuille (2022) for the transformed and scaled outcome variables. These results are compared with Figure 8, which shows the estimates obtained from the original scale of fatalities using the IHS transformation.

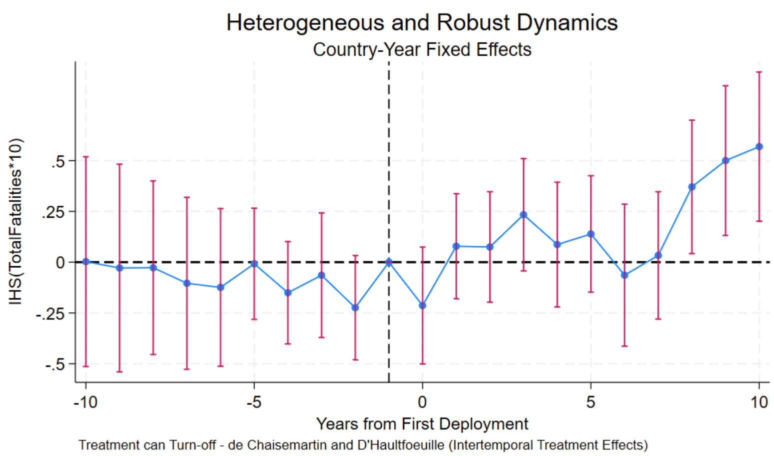



Figure C.3: Robust Event Study with IHS-Transformed and Up-scaled Fatalities

The results for the up-scaled and transformed outcome variable are shown in Figure C.3, while those for the down-scaled and transformed outcome variable are presented in Figure C.4. As Chen and Roth (2023) pointed out, the magnitude of estimated coefficients can change dramatically with rescaling, as rescaling the units of outcome variable before applying a log-like transformation can yield treatment effects of any magnitude when the treatment also affects the extensive margin.

This study's main findings indicate that most estimated coefficients are not significantly different from zero. Therefore, these rescaling effects do not threaten the conclusions established in the main results. The findings consistently show that the intensity of conflict escalates eight to ten years after the initial deployment of peacekeepers when most treated locations no longer have peacekeepers, as

higher standard deviations for up-scaled variables and lower ones for down-scaled variables.

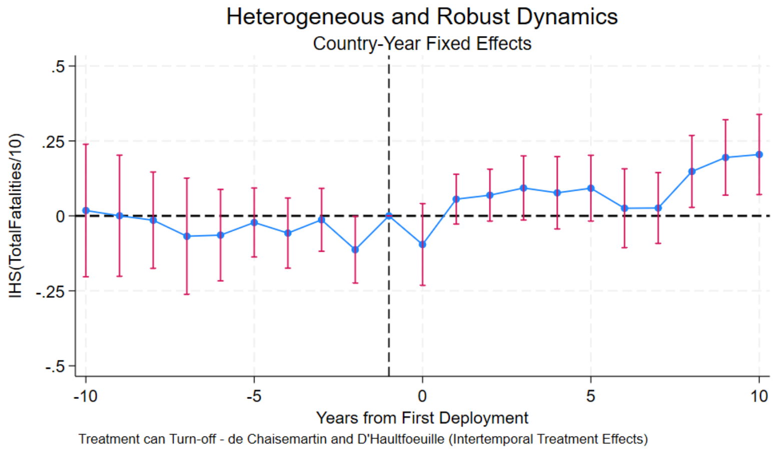



Figure C.4: Robust Event Study with IHS-Transformed and Down-scaled Fatalities

reflected in positive and significant estimated coefficients in the event study. Nevertheless, I refrain from interpreting percentage changes in this context due to the arbitrary nature of the transformed units associated with fatalities. This caution arises from the inherent unit dependence of log-like transformations, as individual-level percentage effects are not well-defined when outcomes shift from zero to nonzero after treatment (Chen & Roth, 2023).

## C.3 Leave-One-Out Robustness Checks

In this section, I perform a leave-one-out analysis by excluding one treated country at a time and re-conducting the analysis using the method outlined by de Chaisemartin and D'Haultfœuille (2022), as described in Section 6.2. This robustness exercise addresses the substantial heterogeneity in UN peacekeeping missions, including variations in mandates and the political contexts in which peacekeepers operate. By excluding one treated country at a time, this analysis helps determine whether the conflict dynamics depicted in Figure 8 are driven by a specific treated country.

The leave-one-out analysis produces 26 subfigures, presented across Figures C.8, C.9, and C.10. Each excluded country aligns with the 29 UN missions covered in the sample, summarized in Table G.1 in Appendix G.

Overall, the results of the leave-one-out analysis indicate no significant differences across subfigures, suggesting that any single treated country does not drive the observed conflict dynamics. Specifically, an escalation in conflict intensity, measured by fatalities, is observed over the long term. However, slight variations emerge in the magnitude and significance of the estimated coefficient for $t = 0$, the year when peacekeepers arrive. In Figures 8 and 11, I concluded that the intensity of conflict decreases during $t = 0$, primarily due to a reduction in one-sided violence. However, when countries such as Rwanda or Mozambique are excluded, the $t = 0$ coefficient is no longer negative (indicating a decrease in fatalities) but approaches zero.

The change in the interpretation of the immediate impact of peacekeepers on conflict fatalities aligns with evidence in the data and historical scenarios in UN peacekeeping operations. For instance, during the United Nations Assistance Mission for Rwanda (UNAMIR, 1993–1996), peacekeepers were unable to prevent the 1994 genocide due to limited troop numbers.[25] The observed decrease in fatalities in the immediate term, in Rwanda specifically, seems primarily driven by the natural subduing of violence following peak atrocities rather than by peacekeepers' direct influence.

This reflects the significant constraints under which peacekeepers often operate. In cases like Rwanda, peacekeepers faced strict limitations on using force, conflicting instructions between the mission and UN headquarters in New York, and significant political constraints that hindered effective action. These limitations meant that peacekeepers struggled to intervene effectively during intense violence. Instead, their role was largely reactive, focusing on stabilization efforts after the intensity of violence had already begun to subside (Williams & Bellamy, 2021).

## C.4 Validation Using Alternative Conflict Data

The primary analyses in this study rely on the UCDP Georeferenced Event Dataset (UCDP-GED) from the Uppsala Conflict Data Project (UCDP) due to its relative accuracy in reporting casualties for major conflict events (Weidmann, 2015). Additionally, its classification of state-based, non-state-based, and one-sided violence aligns with the focus on states as key actors in consenting to peacekeeper deployments.

In this section, I conduct a robustness analysis using an alternative data source on conflict events—the Armed Conflict Location and Event Data (ACLED) (ACLED, 2023). This analysis enables a comparison of results and an evaluation of the consistency of findings across different datasets.

It is important to note that ACLED begins in 1997, compared to UCDP-GED, which started in 1994 and employs different criteria for event inclusion and classification. The ACLED dataset categorizes conflict events into six types: battles, protests, riots, explosions/remote violence, violence against civilians (VAC), and strategic developments. Unlike UCDP-GED, ACLED's inclusion of violent demonstrations and riots extends its focus beyond active armed conflict (Donnay et al., 2019).

[25] Summary statistics of one-sided violence deaths highlight the sharp contrast in fatalities depending on peacekeeper presence: In 1994, areas with peacekeepers present in Rwanda had an average of 39,255 deaths (std: 99,571), compared to 7,183 deaths (std: 8,895) where peacekeepers were absent. By 1995, the average number of deaths in areas with peacekeepers dropped to 11 (std: 35), while regions without peacekeepers reported 671 deaths (std: 1,630). The observed reduction in one-sided violence reflects this stark contrast between 1994 and 1995.

To ensure interpretative comparability, this robustness analysis focuses on fatality outcomes related to battles and violence against civilians (VAC), which closely align with the primary variables of interest in the main analysis. Specifically, state-based and non-state-based conflicts are primarily associated with battles, while one-sided conflicts are predominantly linked to VAC.

Formally, I estimate the following specification with grid-cell and country-year fixed effects, consistent with the approach used in Equation (2):

$$\begin{aligned}\text{ACLED}_{it} = \alpha + \sum_{l=2}^{10} \beta_l^{lead} \text{Arrival}_i \times \mathbb{1}\{\text{lead}_t = \text{l}\} + \sum_{k=0}^{10} \beta_k^{lag} \text{Arrival}_i \times \mathbb{1}\{\text{lag}_t = \text{k}\} \\ + \mathbf{X}_{it}\Gamma + \mu_i + \delta \, \text{Country}_i \times \text{Year}_t + \varepsilon_{it},\end{aligned} \tag{3}$$

where $i$represents the grid cell and $t$ represents the year. The variable $\text{ACLED}_{it}$ captures conflict-related outcomes from the ACLED dataset for a specific cell $i$ in a given year $t$.

Similar to the primary analysis specification, including grid-cell fixed effects in the regression analysis effectively excludes grid cells that never experienced peacekeeping deployments or any observed conflicts in the ACLED dataset. This results in a sample of 4,198 unique grid cells, 385 of which were ever treated, spanning 24 years (1997–2020) and totaling 100,752 observations. In contrast, the main analysis using UCDP data includes 76,788 observations, reflecting that ACLED data likely capture more lower-intensity conflict events, such as protests, riots, and remote violence. Among the events in the ACLED sample, the most prevalent types are battles and violence against civilians (VAC), accounting for 27.2% and 25.1% of events, respectively, which further supports the focus on these outcomes in the robustness analysis.

Figures C.5, C.6, and C.7 present the event study results estimated using Equation (3). These figures illustrate the dynamics of the probability of any conflict event recorded in ACLED, the IHS-transformed fatalities from battles, and the IHS-transformed fatalities from violence against civilians, respectively. Due to differences in the classification criteria of conflict data and the analysis sample, directly comparing the dynamics between the main results and this robustness exercise is less meaningful. Instead, the focus is on examining the contrasting impacts between the extensive and intensive margins, which underscore the deterrence versus intervention effects of peacekeepers.

Figure C.5 shows that deploying peacekeepers does not significantly change the likelihood of conflict events. If any effect exists, the possibility of conflict initially increases slightly before declining; however, the estimated coefficients during the early periods are not statistically significant. Around the fourth year following the initial presence of peacekeepers, the likelihood of conflict becomes significantly lower, providing evidence that peacekeepers exert a deterrence effect associated with their presence.

Regarding the intensive margins associated with fatalities, Figures C.6 and C.7 reveal nuanced dynamics. For battle-related fatalities, peacekeeper deployment appears to be associated with significantly fewer battle deaths between the fourth and seventh years after their initial deployment. At the same time, other periods show no significant differences. In contrast, the results for violence against civilians suggest an increase in civilian fatalities immediately following peacekeepers' initial deployment, particularly during the first year, with limited impact observed in the long term. These findings underscore the constrained intervention effects of peacekeepers in actively reducing fatal violence against civilians. Additionally, the short-lived reduction in battle-related deaths further highlights the limitations of peacekeepers' ability to sustain long-term intervention impacts locally.

Overall, even with a different source of conflict event data and an alternative sample (ACLED instead of UCDP-GED), the results of this robustness exercise confirm the conclusions drawn from the primary analyses. Specifically, peacekeepers demonstrate a deterrence effect, reducing the likelihood of conflict events. However, when it comes to direct intervention in fatal battles or intense violence against civilians, the principles of UN peacekeeping constrain peacekeepers' ability to effectively respond and prevent these fatal clashes.

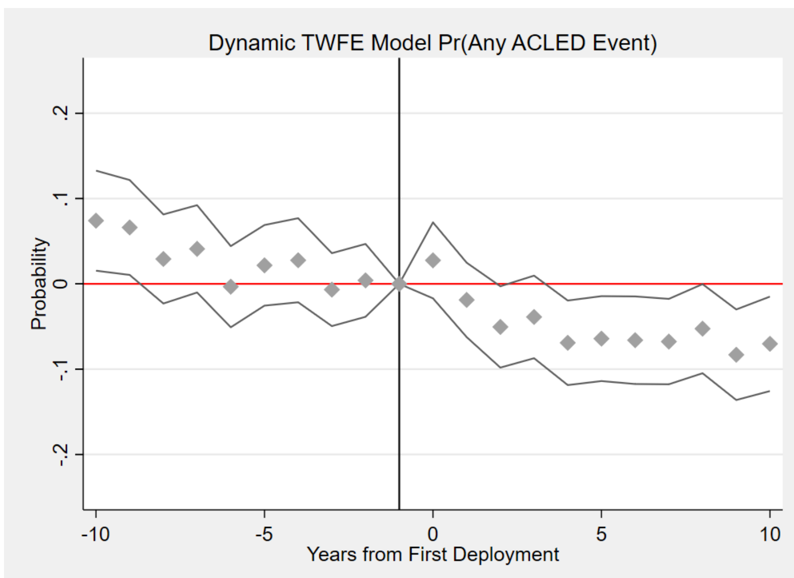



Figure C.5: Event Study with Extensive Margin using ACLED

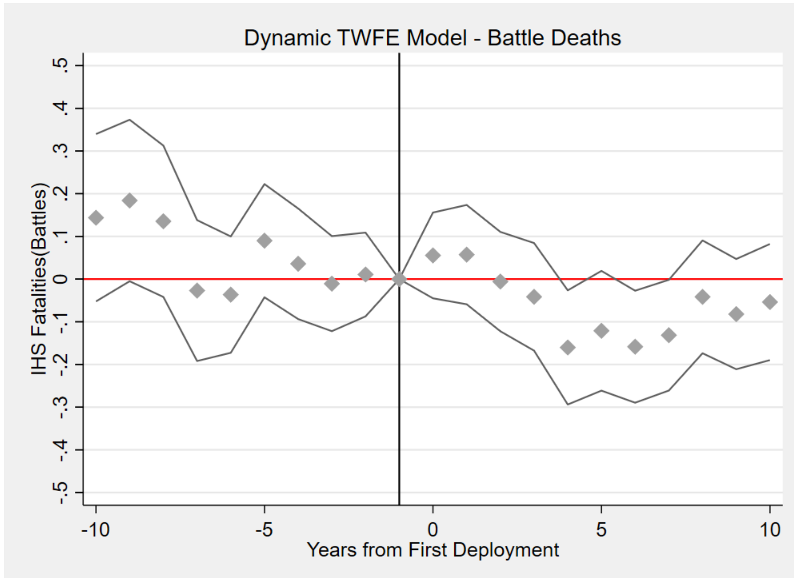



Figure C.6: Event Study with Intensive Margin on Battle Deaths using ACLED

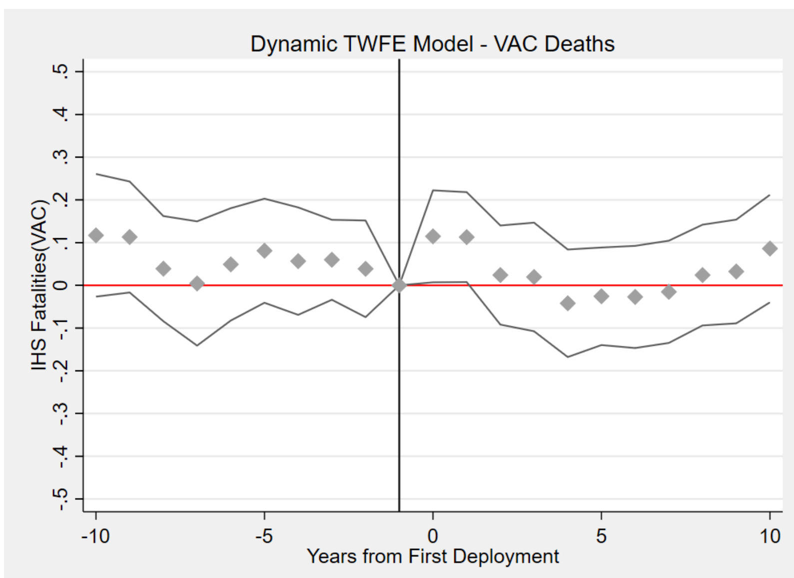



Figure C.7: Event Study with Intensive Margin on VAC Deaths using ACLED

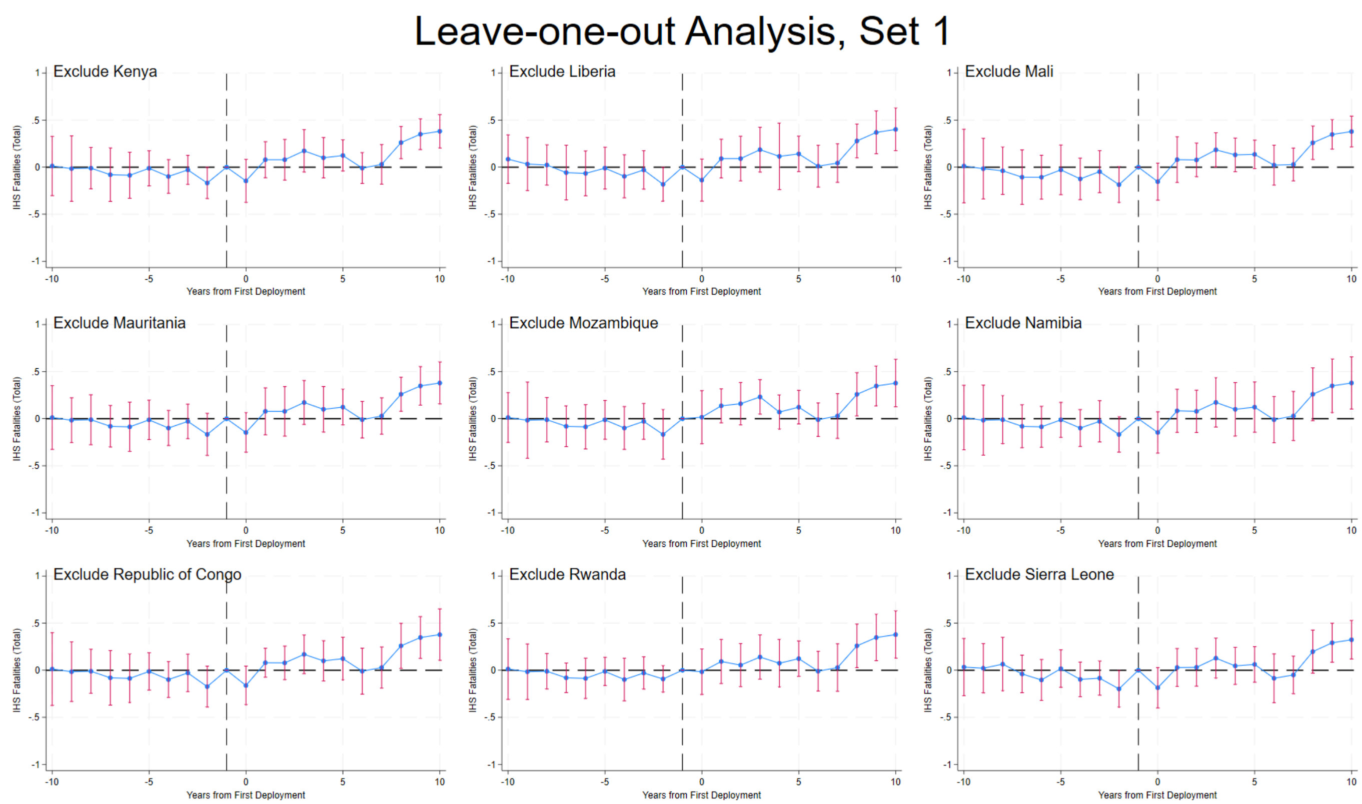



Figure C.8: Non-absorbing Treatment and the Dynamics of Conflict Intensity, Part 1

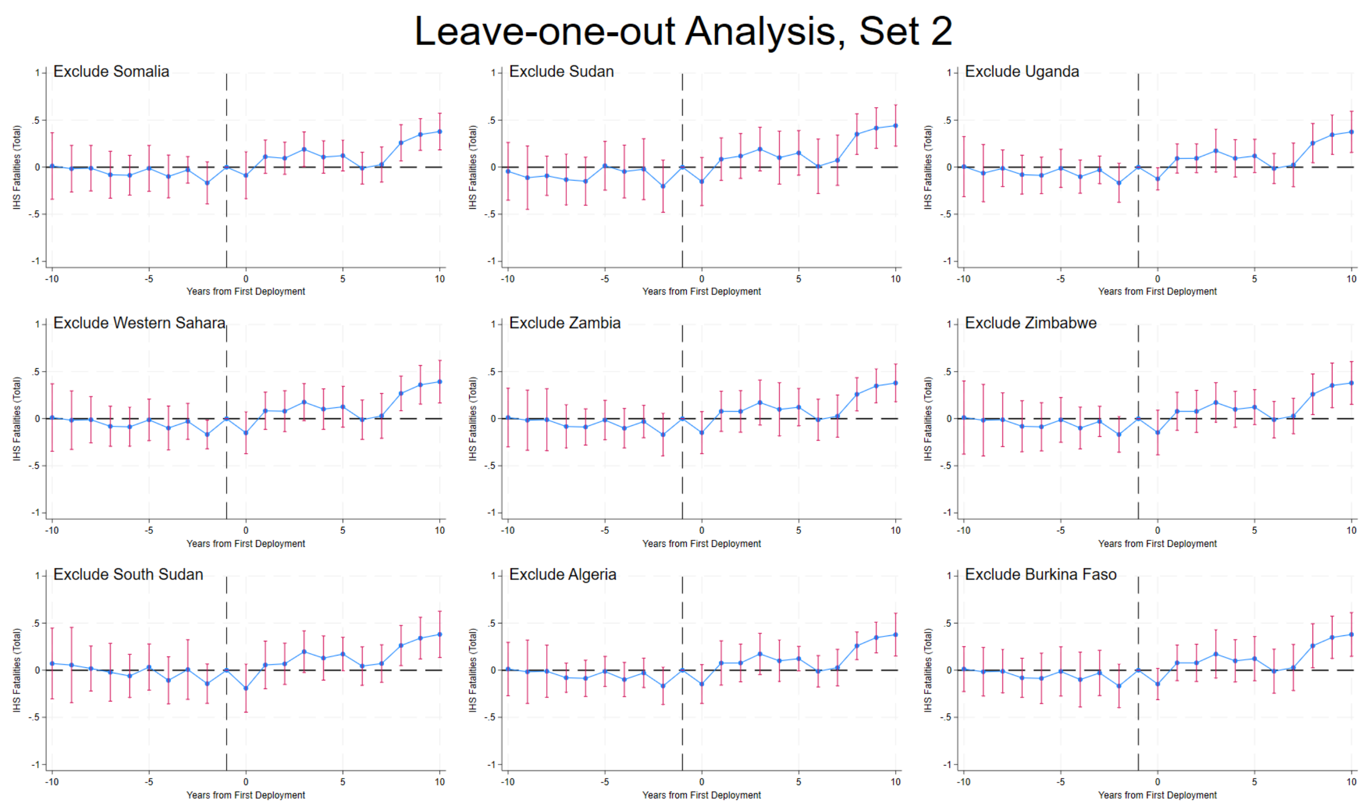



Figure C.9: Non-absorbing Treatment and the Dynamics of Conflict Intensity, Part 2

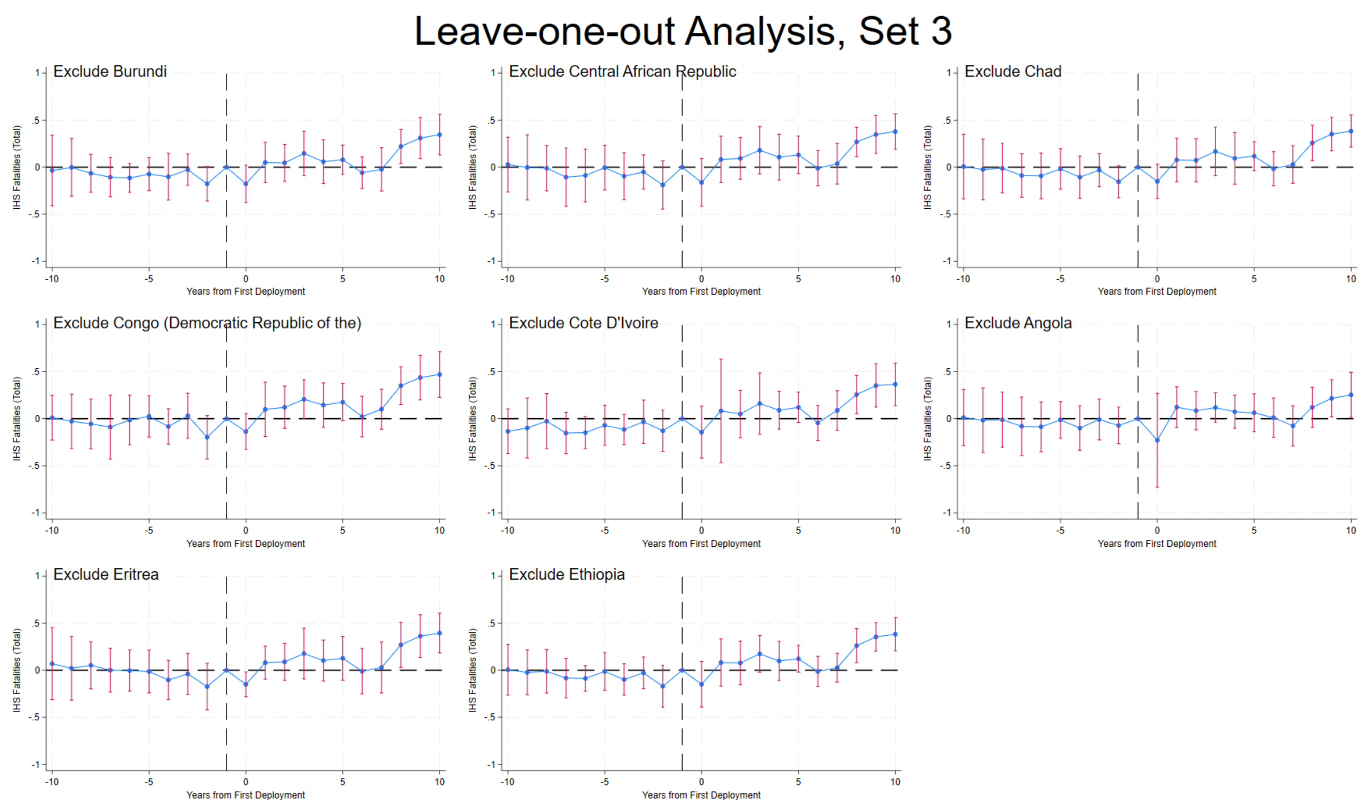



Figure C.10: Non-absorbing Treatment and the Dynamics of Conflict Intensity, Part 3

# Appendix D Supplementary Information: MONUSCO

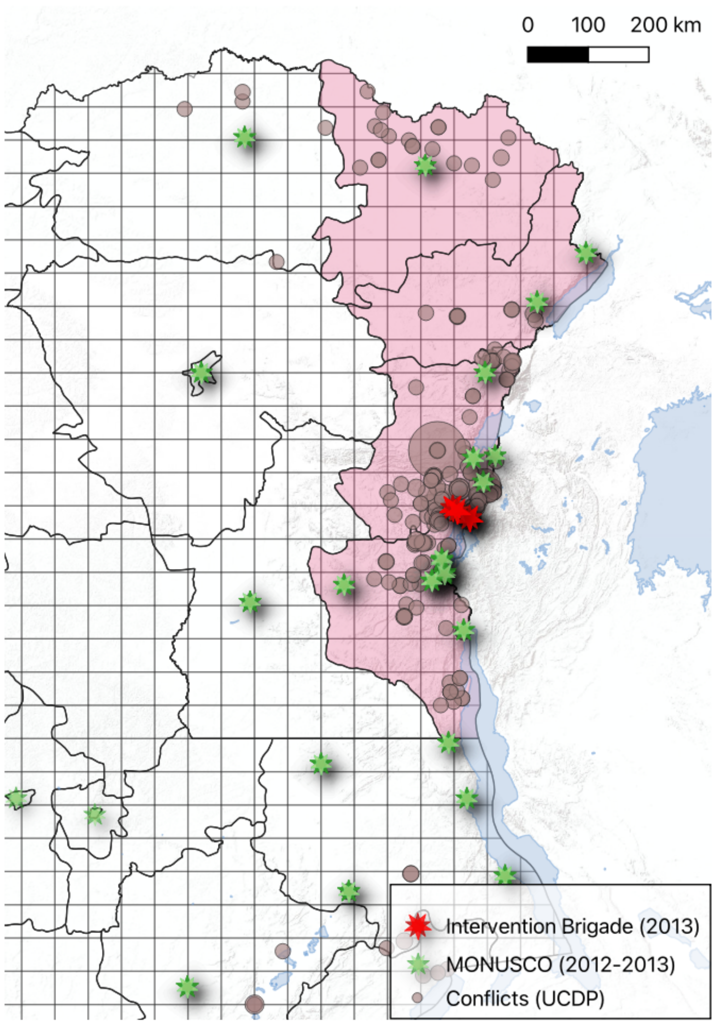
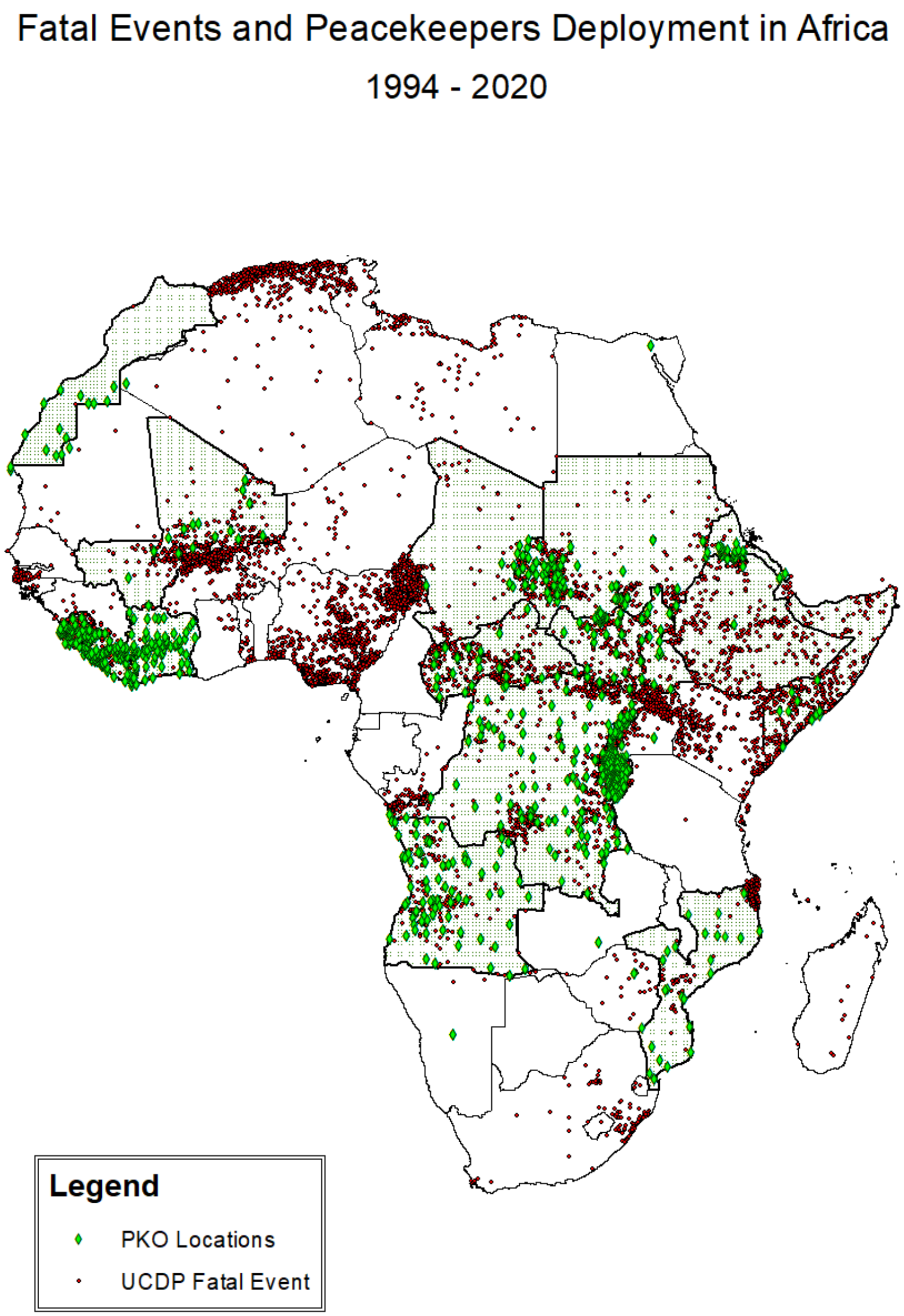



Figure D.1: MONUSCO Presence and UCDP Conflict Events in Eastern DRC (2012-2013)

## Appendix E Map



# Appendix F Data Description

The table describes the variables used in the summary statistics and the regression analysis.

| Regression Var. (Source) | Description |
|---|---|
| Fatalities (UCDP-GED) | The number of fatalities is the best (most likely) estimate of total deaths resulting from an event, which is the sum of the best estimates from the conflicting parties, civilians, and people with unknown status. The fatalities are linked to the event, which could be mapped into grid cells and aggregated to yearly level. (Stina, 2022; Sundberg & Melander, 2013) |
| Type of Violence (UCDP-GED) | UCDP defines three-type of violent events, including state-based armed conflict, non-state conflict, and one-wided violence.<br>State-based armed conflict referes to the disputes involving government or territory that leads to the use of armed force between two parties, with at least one being a state government.<br>Non-state conflict refers to a situation in which armed force is used between two organized armed groups, neither of which represents a state government.<br>One-sided violence involves the use of armed force by the state government or by a formally organized group against civilians. (Stina, 2022; Sundberg & Melander, 2013) |
| Deployment (Geo-PKO) | A binary variable based on the Geo-PKO dataset between 1994 to 2020, if there were peacekeepers deployed to the location (latitude and longitude) in a given year, the grid covering the specific location is counted as treated in the given year. |
| Temperature (ERA5) | Desmet et al. (2023) calculated the annual mean temperature (in degrees Celsius) for each cell using monthly meteorological data from the ERA Reanalysis dataset (Muñoz-Sabater et al., 2021). To ensure comparability among cells, the standardized temperature deviations at the yearly level are used. |
| Precipitation (ERA5) | ERA 5 provides monthly averaged precipitation data (in mm). To ensure comparability of the measure across cells, the double-standardized rainfall deviations are used. Desmet et al. (2023) first account for seasonal patterns by standardizing monthly rain totals by cell and month for the period 1989–2020. For each cell, these indicators are then summed up by year and standardized over the same period. |
| Nightlights (DSMP) | The Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) provides nighttime light data. These data capture the artificial light emissions from human settlements related to economic activities, urbanization, and development patterns. DMSP-OLS data are collected by satellites orbiting Earth for global coverage and long-term observations (Baugh et al., 2010; C. Elvidge et al., 1997). |

Table F.1: Details of Variables used in the Regression Analysis

| Summary Var. (PRIO-GRID) | Description |
|---|---|
| Nightlights | See Table F.1 |
| Distance to Own Border | This variable represents the shortest distance in kilometers from the cell's center to the territorial boundary of the country it belongs to. For cells located along a coast or in island states like New Zealand, it measures the distance to international waters (Weidmann et al., 2010). |
| Distance to Capital | The variable provides the spherical distance, in kilometers, from the cell centroid to the national capital city within the corresponding country, using their coordinates (Weidmann et al., 2010). |
| Mountainous Area | It quantifies the fraction of mountainous terrain within the cell, using elevation, slope, and local elevation range data sourced from a high-resolution mountain raster from UNEP's Mountain Watch Report (Blyth et al., 2002). |
| Time to the Nearest Town | The variable caputres the mean travel time (in minutes) to the closest major city (a population exceeding 50,000 inhabitants), derived from a global raster map created for the EU. This indicator results from network analysis, combining data from various sources, primarily collected between 1990 and 2005 (Uchida & Nelson, 2009). |
| Population Density | This variable is calculated by dividing the population size by the land area of the grid. The population size data is originated from the Gridded Population of the World v.3. The original population data is a raster data, the population is thus summed up to obtain the total population in the grid (Center for International Earth Science Information Network & Centro Internacional de Agricultura Tropical, 2005). The land area is derived from CShapes dataset (Weidmann et al., 2010) measured in square kilometers. |
| Excluded Ethnic Groups | The variable represents the count of excluded groups, referring to discriminated or powerless communities, specifically the status and location of politically relevant ethnic groups residing in the grid cell for the respective year, originally sourced from the GeoEPR/EPR 2014 update 2 dataset (Vogt et al., 2015). |

Table F.2: Details of Variables used in Summary Statistics

# Appendix G Overview of UN Peacekeeping Missions

| Acronym | Full Name (with Hosting Country) | Start | End |
|---|---|---|---|
| UNAVEM II | United Nations Angola Verification Mission Il | Jun-91 | Feb-95 |
| UNAVEM III | United Nations Angola Verification Mission III | Feb-95 | Jun-97 |
| MONUA | United Nations Observer Mission in Angola | Jun-97 | Feb-99 |
| ONUB | United Nations Operation in Burundi | Jun-04 | Dec-06 |
| BINUB | United Nations Integrated Office in Burundi | Jan-07 | Jan-11 |
| MINURCA | United Nations Mission in the Central African Republic | Apr-98 | Feb-00 |
| MINURCAT | United Nations Mission in the Central African Republic and Chad | Sep-07 | Dec-10 |
| MINUSCA | United Nations Multidimensional Integrated Stabilization Mission in the Central African Republic | Apr-14 | Present |
| MONUC | United Nations Organization Mission in the Democratic Republic of the Congo | Nov-99 | Jun-10 |
| MONUSCO | United Nations Organization Stabilization Mission in the Democratic Republic of the Congo | Jul-10 | Present |
| UNTSO | United Nations Truce Supervision Organization (Egypt & Middle East) | May-48 | Present |
| UNMEE | United Nations Mission in Ethiopia and Eritrea | Jul-00 | Jul-08 |
| MINUCI | United Nations Mission in Côte d'ivoire | May-03 | Apr-04 |
| UNOCI | United Nations Operation in Côte d'ivoire | Apr-04 | May-17 |
| UNOMIL | United Nations Observer Mission in Liberia | Sep-93 | Sep-97 |
| UNMIL | United Nations Mission in Liberia | Sep-03 | Mar-18 |
| MINUSMA | United Nations Multidimensional Integrated Stabilization Mission in Mali | Apr-13 | Dec-23 |
| MINURSO | United Nations Mission for the Referendum in Western Sahara | Apr-91 | Present |
| ONUMOZ | United Nations Operation in Mozambique | Dec-92 | Dec-94 |
| UNOMUR | United Nations Observer Mission Uganda-Rwanda | Jun-93 | Sep-94 |
| UNAMIR | United Nations Assistance Mission for Rwanda | Oct-93 | Mar-96 |
| UNOMSIL | United Nations Observer Mission in Sierra Leone | Jul-98 | Oct-99 |
| UNAMSIL | United Nations Mission in Sierra Leone | Oct-99 | Dec-05 |
| UNIOSIL | United Nations Integrated Office in Sierra Leone | Jan-06 | Jan-08 |
| UNOSOM II | United Nations Operation in Somalia II | Mar-93 | Mar-95 |
| UNMIS | United Nations Mission in the Sudan | Mar-05 | Jul-11 |
| UNAMID | African Union-United Nations Hybrid Operation in Darfur (Sudan) | Jul-07 | Dec-20 |
| UNISFA | United Nations Organization Interim Security Force for Abyei (Sudan-South Sudan) | Jun-11 | Present |
| UNMISS | United Nations Mission in the Republic of South Sudan | Jul-11 | Present |

Table G.1: All 29 UN Missions in Africa and Their Operational Periods (1994 to Present, as of December 2023)

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