Conflict Grids and Peacekeeping: When and Where Do Peacekeepers Keep the Peace?*

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Abstract

When, and more importantly where, do United Nations (UN) peacekeepers (PKs) keep the peace? UN Peacekeeping Operations (PKOs) often deploy to protect civilians and separate belligerents. However, much of the research uses country-level aggregate data that fails to consider the geospatial effects of violence dispersion and assumes peacekeepers are spread evenly inside a country's borders. More recent analyses have utilized disaggregated geospatial data to see whether peacekeeping reduces violence against civilians at a more local level (Fjelde, Hultman, and Nilsson 2019). However, those analyses rely on a dependent variable of violence that is likely underreported and fail to account for several effects endogenous to the peace process. Using the ACLED's violence data combined with RADPKO's data on the UN's peacekeeper movement, I employ a spatially disaggregated model analyzing when and where peacekeepers reduce violence against civilians. This paper is unique in the peacekeeping effectiveness literature in that it utilizes more advanced methods for comparing locations exposed and unexposed to peacekeepers. In particular, it combines recent advances in optimal matching with multilevel analysis. This research finds that peacekeepers only substantively reduce violent events from government actors, contradicting the existing literature while providing an innovative contribution. I conclude by discussing the implications, especially questioning the mechanisms assumed by prior research to cause peacekeeper violence reduction, and discussing the need to evaluate them in a narrower and qualitative setting.
Keywords: UN, peacekeeping, conflict research

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*Working paper; please do not circulate.

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1 Introduction

Despite consisting of an international conglomeration of the world's troops and requiring unanimous consent from the permanent five (P5) members of the Security Council to operate, the United Nations' (UN's) worst actions are magnified due to the profile and status of the organization. The Rwandan genocide stands out as one of famously poor decision making by both the UN and its member states; several Belgian peacekeepers (PKs) "believed that there were virtually no circumstances in which they could legitimately fire their weapons,"[1] and many soldiers stood by and helplessly watched the ethnic cleansing. Despite this reputation of uselessness, the UN spends more than $6 billion annually on PKOs and constantly renews the missions for more work.[2] This fuels a puzzle: do peacekeepers keep the peace? Peacekeeping missions receive massive amounts of funding, and 13 peacekeeping operations (PKOs) are currently active throughout the world, indicating the UN believes, at some level, in the effectiveness of peacekeepers. Can peacekeepers prevent violence against civilians by either state or rebel forces when tasked with it? When PKOs deploy, civilian protection often falls exclusively on the shoulders of its peacekeepers.

Since the end of the Cold War in the early 1990s, UN Peacekeeping Operations (PKOs) have dramatically increased in both size and scope. These PKOs often deploy in the interests of protecting civilians and separating belligerents, yet most of the research done relies on national data aggregated by quarter or year. More recent analyses have utilized disaggregated geospatial data to see whether peacekeeping reduces violence against civilians at a more local level.[3] However, those analyses rely on a dependent variable of violence that likely underreports the actual amount of violence against civilians and fails to account for several effects endogenous to the peace process.

While the public and news media seem to have made up their minds about peacekeeping effectiveness, academics have come to the opposite conclusion. More recent studies such as Fjelde, Hultman, and Nilsson 2019, Beardsley and Gleditsch 2015, and Ruggeri, Dorussen, and Gizelis 2017 all use the Uppsala Conflict Data Program's (UCDP) Georeferenced Dataset (GED); I argue that the UCDP's threshold for deaths, measured at "all cases where one-sided violence by an armed actor reaches an annual twenty-five-fatality threshold," is relatively arbitrary in terms of measuring violence and will tend to undercount violence. Peacekeeping matters not because it can prevent large numbers of deaths in the locales PKs deploy to; rather, it matters because PKs have the opportunity to, and are often mandated to, protect civilians.

Methodologically speaking, this paper contributes to the peacekeeping effectiveness literature in two distinct ways. First, this research improves the measurement of violence against civilians. The data utilizes a substantially larger N than the next closest analysis. Fjelde et al. (2019) identified 159 grids

1. **https://www.hrw.org/reports/1999/rwanda/Geno15-8-01.htm**.
2. **https://peacekeeping.un.org/en/how-we-are-funded**.
3. Fjelde, Hultman, and Nilsson 2019.

in their dataset with one-sided violence and 214 with peacekeepers; I improve on this by aggregating data from the Robust Africa Deployments for Peacekeeping Operations (RADPKO) and Armed Conflict Location and Event Database (ACLED), which provides a dataset of 838 grids that experience one-sided violence and 271 with peacekeepers. A larger N study allows for a more robust result from my analysis. Beyond more data points, I improve the measurement of violence by disaggregating deaths and violent events and further explain why Fjelde et al. (2019) make several unjustified assumptions in creating and measuring the dependent variable (DV). They measure violence against civilians with a dichotomous outcome of whether five civilians died in a single month or not.

In contrast, I expand upon Fjelde et al.'s knowledge by using a DV with a count variable of violent events and deaths using a negative binomial regression. I also acknowledge that simple measures of political violence reduce the lived experiences of those affected by violence (Nyseth Brehm, O'Brien, and Wahutu 2021). Ultimately, I improve the measurement by utilizing a multilevel model that accounts for grid and country-level mission differences. Second, this paper is unique in the peacekeeping effectiveness literature in that it utilizes more advanced methods for comparing locations exposed and unexposed to peacekeepers. In particular, it exploits recent advances in optimal matching to address several methodological concerns further explained in the research design section later on. In short, I utilize cardinality matching rather than propensity score matching to reduce the reliance on parametric model assumptions and to improve the hidden bias sensitivity tests.([4]

This paper proceeds as follows. First, I review the previous contributions to the peacekeeping effectiveness literature, focusing on analyzing the papers that have utilized geospatial techniques with disaggregated, sub-national data. Next, I outline my research design and data, explaining why and how both are instrumental in determining causal relationships in the most advanced methods used in the peacekeeping literature. Finally, I analyze the results of my models, explaining their implications and where future scholars should proceed from here.

2 Other PKO Research & My Contributions

2.1 Previous Literature

Hultman et al.'s oft-cited article argues that UN troops and police reduce the amount of violence against civilians while observers cause an increase in violence.[5] Bara and Hultman 2020 compares UN and non-UN peacekeeping and shows that UN peacekeepers are the only actors between the two that prevent violence against civilians by non-state actors. However, these analyses and others tend to use data on peacekeepers granular to the country level and often measure in year intervals. If measured at the

4. Carreras, Vera, and Visconti 2022.
5. Hultman, Kathman, and Shannon 2013 point out that this is likely because UN observers are unarmed indicate a lack of commitment by the international community to peace, showing belligerents that their actions likely will not have dire consequences.

year level, this sets up a substantively significant assumption that peacekeepers are distributed evenly throughout the year, which is patently false. Peacekeeping missions are notorious for having varying levels of peacekeepers, as troop-contributing countries often send troops late or pull them out before the UN's mandated arrival or exit date.

While this assumption biases the data one way, the other assumption made by most of the literature biases the data geospatially. All of the earlier quantitative work on peacekeeping effectiveness, including the most influential PK effectiveness articles such as Hultman, Kathman, and Shannon 2013, utilizes data aggregated at the country level. In other words, it assumes that peacekeepers and violence are spread evenly across the country, from states as small as Burundi to as large as the Democratic Republic of the Congo (DRC), with the latter possessing eighty-four times the area than the former.[6] This assumption, of course, cannot be accurate due to variations in troop size, mission mandates, and even topography. Beyond that, treating each country as functionally the same ignores the possibility of endogeneity present; i.e., violence in one country is likely caused by different factors than violence in another, notwithstanding the fact that violence spillover may occur, violating the independence assumption. Because the causes of violence are not randomly distributed, this affects the outcome and biases the results.

More recent studies have used instrumental variables to assess whether there is an effect of peacekeeping and to avoid issues of endogeneity. Carnegie and Mikulaschek 2020 point out that "since international intervention is not randomly assigned," there might be a reason why peacekeepers go to some places over others that ultimately affects violence against civilians.[7] For example, if a peacekeeping mission is being deployed, this could signal to the international community that the state is a safe investment for various economic investments such as foreign direct investment. Increasing the capital and funds available to the country could make it more stable and prosperous, ultimately decreasing the violence through a different mechanism than directly through peacekeepers. Addressing this issue, Carnegie and Mikulaschek 2020 use an as-if random variation of the rotating seats on the security council as an instrument. While this ultimately gives them sufficient reason to determine that peacekeepers reduce the amount of violence against civilians by rebel groups, this does not solve the geospatial distribution issue discussed above. A country-level aggreagation is blind to local-level variations in peacekeeping deployments, both in space and in deployment numbers of peacekeepers. Futhermore, Carnegie and Mikulaschek's causal mechanism applies to the country level, but does not tell us why peacekeepers affect violence against civilians at a local level. This assersition is supported by Shesterinina and Job 2016, who show in Côte d'Ivoire and Somalia that some groups of civilians received protection while others do not, further proving that the UN has institutional reasons for not deploying peacekeepers evenly, even to similarly sized groups of civilians.

Multiple articles detail the local effects of peacekeeping, such as Beardsley and Gleditsch 2015 and

6. From CIA Factbook DRC and CIA Factbook Burundi
7. 811

Peitz and Reisch 2019 identifying the conflict displacement of UN PK forces between rebel-government dyads, and Ruggeri, Dorussen, and Gizelis 2017 examining how local PKs effect the duration of violence. However, the only article so far to examine the local effects of PKs on violence against civilians is Fjelde, Hultman, and Nilsson 2019. Fjelde et al. find that "even when accounting for the non-random selection of peacekeepers to a location, their presence has a negative and significant effect on reducing the risk of violence against civilians by rebel actors."[8]

Nonetheless, Fjelde et al.'s paper, while important and a good contribution to the literature, makes several concessions and assumptions that are not supported by the data while using relatively outdated research methodology. First, they use propensity score matching, AKA greedy matching, to account for the non-random deployment of peacekeepers. Their justification for this is appropriate, as treating areas peacekeepers were and were not deployed to as functionally the same inherently biases the DV of violence against civilians since other reasons could plausibly be causing PK deployment to those areas. Fjelde et al. correctly point out that peacekeepers might deploy more to higher violence areas, making it seem like peacekeeping increases violence, or they might deploy to lower violence areas, thus influencing the outcome towards peacekeeping as effective. While propensity score matching is not inherently flawed, it can necessarily only match based on observed covariates, which ignores the possibility of unobserved sorting of other variables not included by the researchers. Furthermore, King and Nielsen 2019 outline several reasons why propensity score matching often increases bias, showing that greedy matching often "increases imbalance, inefficiency, model dependence, research discretion, and statistical bias."[9]

In a second bias coming from the research design, Fjelde et al. measured violence against civilians through a dichotomous DV "where five or more civilians were killed in a given grid cell in a given month." [10] Measuring violence this way biases the data and conclusions in two distinct ways. First, I argue that the 5-death threshold used is too restrictive and not precise enough to measure violence against civilians accurately. Ignoring smaller counts of violence bias the estimates if the variable of interest is the total number of deaths; this will result in under-counting the violence, which will bias the estimates higher and show a more substantive effect of peacekeeping without an identical under-counting of peacekeepers. Second, I take issue with how the authors operationalize "violence" against civilians. While civilian death is a relatively standard measure of one-sided violence (OSV) in the literature, it is not accurate to use death as the sole measure of violence.

Additionally, restricting the DV to mere deaths while labeling it as "violence" misleads readers to assume that peacekeepers successfully reduced the amount of violence against civilians. Definitions matter, and so do the words we use. As a researcher, saying that the only violence that matters is when at least five civilians are killed shows an inherent bias in the definition; violence as a whole matters, not

8. 125
9. 435
10. 112

just the extreme cases. Measuring deaths while claiming to measure violent events misrepresents the data and further misrepresents the actual effects of peacekeeping.

2.2 Methodological Contributions

This paper makes two contributions to the quantitative peacekeeping literature. Broadly, I do this by improving upon the measurement and concepts used to find the estimation and by testing the causal claims against a dataset never used before in this literature. First, I utilize improved measurement with a unique data source, specifically compared to Fjelde, Hultman, and Nilsson 2019. As discussed in the literature review earlier, Fjelde, Hultman, and Nilsson 2019 make several broad assumptions that the data does not support. Among those assumptions are that, beyond troop deployment numbers, Chapter VII missions do not vary in a meaningful way and thus do not account for these issues. Discussed more in the methods section, I apply a multilevel model to handle the potential variation in country and mission across time.

Additionally, I utilize recent innovations in matching to obtain a sample as close as possible in covariate balance. While using cardinality matching reduces ”concerns about extrapolation based on parametric models,”[11] it is vital to note that this does not inherently allow for causal claims. However, it is one of many critical methodological contributions I bring to the peacekeeping literature and is something that future scholars would do well to replicate.

Regarding the dependent variable, I adjust the variable of interest from Fjelde, Hultman, and Nilsson 2019. They use a dependent variable of violence against civilians, coded as a ”1” if five or more civilians were killed by either a rebel or government group in a grid in a given month and 0 otherwise. Fjelde, Hultman, and Nilsson 2019 find that, when measuring the DV this way, peacekeepers are effective at reducing violence against civilians by rebel groups but not by government groups. However, as noted in Walter, Howard, and Fortna 2021, to advance our knowledge of peacekeeping, scholars need to disaggregate the data as much as possible to understand when and where peacekeepers are effective. Other researchers such as Nyseth Brehm, O'Brien, and Wahutu 2021 point out the need for scholars to refrain from using oversimplified measures when studying violence. Treating violence as a dichotomous outcome of *it either happened or did not* reduces the lived experiences of marginalized groups and should be avoided when possible.

I further the peacekeeping effectiveness literature by separating the DV of violence against civilians and measuring it in several ways. For example, I measure violent events against civilians in two models, one that measures violent events and one that measures deaths. I further separate the models by examining the DV with a count model while also running a robustness check replicating the five death threshold used by Fjelde, Hultman, and Nilsson 2019.

11. Carreras, Vera, and Visconti 2022:12

Second, I contribute methodologically to the existing literature by modifying the data source for violence data. This research diverges from previous papers such as Ruggeri, Dorussen, and Gizelis 2017 & Fjelde, Hultman, and Nilsson 2019 that use the UCDP GED to measure violence against civilians. Since the UCDP is likely to undercount violence, I argue it does not present a hard enough hypothesis test. The ACLED does not lend itself easily to combine with RADPKO's grid system since Raleigh et al. 2010 provides coordinates instead of using the PRIO-Grid system. Nevertheless, ACLED's data robustness and precision, including the measurement of all violent events rather than deaths alone, assist this research in advancing our understanding of peacekeeping effectiveness. Even more importantly, all of my scripts are easily replicable,[12] meaning that any future researchers using ACLED's data, or any other coordinate-based data source, can use it to assign PRIO-grids to their data. Finally, a working paper by Raleigh and Kishi, n.d. also discusses that, when it comes to data collection on violence, none of the four primary violence datasets other than the ACLED consistently meet necessary standards for "methodology, human oversight and expertise, and (an) extensive source network" (29).

3 Research Design

3.1 The Data

To further understand when and where peacekeepers save civilian lives, scholars need accurate and disaggregated sources of data on both violence against civilians and UN peacekeeper movement. Other papers such as Fjelde, Hultman, and Nilsson 2019, Beardsley and Gleditsch 2015, and Ruggeri, Dorussen, and Gizelis 2017 all use the UCDP Georeferenced Dataset (GED) from the Uppsala Conflict Data Program.[13] However, I argue that the UCDP's threshold for deaths, measured at "all cases where one-sided violence by an armed actor reaches an annual twenty-five-fatality threshold,"[14] will result in undercounting of violence. Peacekeeping matters not because it can prevent large numbers of deaths in the locales PKs deploy to; it matters because PKs have the opportunity to, and are often mandated to, protect civilians. More specifically, using the UCDP to analyze violence against civilians biases the resulting analysis in two ways.

First, estimating the causal effects of peacekeepers at a local level requires a hard test. Important to note is that the UCDP "has a strong bias towards undercounting."[15] While the UCDP is generally better at avoiding duplicate data than the ACLED,[16] undercounting the violence would make peacekeeping seem more effective than it is. Previous papers have shown that peacekeepers protect civilians at an aggregated, country-level analysis[17]; therefore, to further break down the data and understand when and

12. Located in the supplementary materials
13. Raleigh et al. 2010.
14. Fjelde, Hultman, and Nilsson 2019.
15. cite Stepanova (2009)
16. Eck 2012.
17. Carnegie and Mikulaschek 2020; Hultman, Kathman, and Shannon 2013.

where peacekeepers are effective, we should begin with a hard test of the assumption that peacekeepers prevent violence against civilians. Suppose we find that peacekeepers reduce violence against civilians, which provides substantial evidence of the causal logic. Suppose we find that peacekeepers do not have a significant or substantive effect. In that case, further research should examine the logic with qualitative approaches and that other potential reasons, such as signaling and deterrence, should be examined as the possible reasons PKOs reduce violence against civilians. The second reason I avoid the GED is that the UCDP only measures deaths rather than violent events. As addressed earlier, violent events that do not result in deaths are still important. Thus, I use ACLED's violent event and death data to measure violence.

ACLED The Armed Conflict Location and Event Database (ACLED)[18] provides data on violence and conflict throughout the world. Specifically, ACLED assembles the data with various sources and reliability checks.[19] For example, the coding guidelines are thorough and provide layers of reliability and inter-coder checks to ensure accuracy. Some of the metadata for each event includes unique ID numbers, time and location precision scores, notes of the event, and the actors who participated. This source provides me with the information needed to add several control variables.

Table 1: ACLED Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Year	42,946	2011.5	5.7	1999	2008	2016	2018
Time Precision	42,946	1.2	0.5	1	1	1	3
Geo Precision	42,946	1.3	0.6	1	1	2	3
Deaths	42,946	3.4	22.9	0	0	2	1,000

Furthermore, ACLED compiles the data via four distinct types of sources: traditional media, reports from institutions and NGOs, local trusted partners that report violence, and so-called "new media" such as Twitter or Telegram, where ACLED verifies and establishes connections with all sources. This provides an incredibly comprehensive data source for violence data. ACLED's data is not generally available to the public, but they do provide access to their robust longitudinal data for researchers. I received data on my countries of interest (further noted in the RADPKO Data section) from 1998 to 2021 and then subsetted the data to the RAPKO dates within RStudio.

I must also address the various criticisms of geo-locational databases such as ACLED and how they are often not the best representations of reality. Eck 2012 points out valid criticisms of both the ACLED and the UCDP's GED dataset. For example, ACLED has a higher rate of duplicate information than the GED data. I maintain my use of ACLED's data for two specific reasons. First, and most importantly, ACLED records violent events and deaths. As mentioned earlier in this article, measuring violence

18. Raleigh et al. 2010.
19. See ACLED's "Methodology" section of their website: https://acleddata.com/

against civilians requires different measures of violent events. Measuring violent events is essential and can still show PKO's effectiveness on violence. For example, it is possible that while peacekeepers do stop rebel groups from killing civilians, as Fjelde, Hultman, and Nilsson 2019 conclude, it is also possible that PKs only deter rebels from committing acts of violence so brutal that they kill civilians while still committing less violent offenses. While this violence may be less severe, it is necessary to know whether peacekeepers can prevent those acts of violence as well. Additionally, as Walter, Howard, and Fortna 2021 point out, while it has been broadly shown that peacekeepers reduce violence against civilians, it is necessary to tease out the effects of when and where they reduce violence—further developing the conceptual bounds of how we measure this violence requires more disaggregation of the violent events we claim to measure, which is only available through ACLED's data.

Second, ACLED's higher duplicate data count will present a more demanding test for the literature's previous expectations. This will bias the analysis of peacekeeping effectiveness as less effective, meaning we can draw more substantively significant conclusions if our results show statistical significance. Again, because analyses such as Carnegie and Mikulaschek 2020 have definitively concluded that peacekeepers protect civilians at a national level, examination of peacekeeper protection of civilians requires a hard test to see if previous causal logics extend to explain how peacekeepers stop violence locally. ACLED provides us with the data to test that hypothesis moreso than the UCDP.

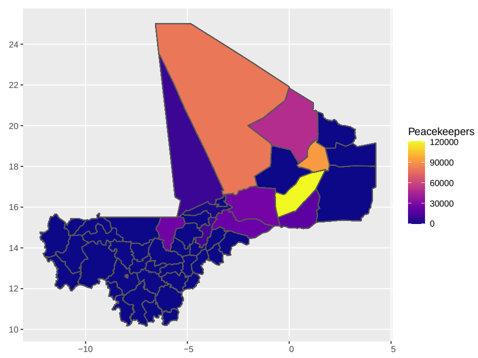
RADPKO The majority of the quantitative literature that covers UN PKO effectiveness almost exclusively analyzes data at the country level. In using data aggregated at this level, researchers assume that the spatial distribution of peacekeepers and violence is evenly spread around the nations they deploy to, primarily because of a lack of available data. However, the Robust Africa Deployments for Peacekeeping Operations (RADPKO) provides information on UN PKOs throughout sub-Saharan Africa. Hunnicutt and Nomikos 2020 put together the RADPKO dataset because of an "empirical levels-of-analysis-problem and divergent sampling strategies"[20] present in the existing quantitative literature. I use RADPKO because it focuses on the disaggregation of peacekeeping forces in various practical ways.

Table 2: RADPKO Summary Statistics

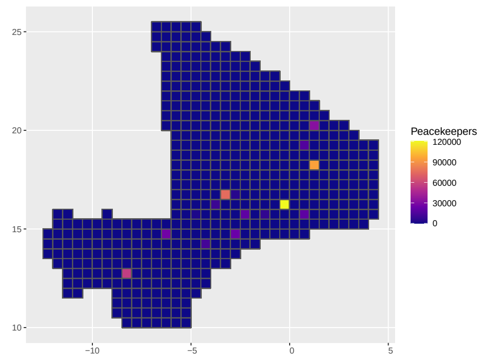
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Total PKs	18,353	612.09	838.38	0	162.67	664.44	6,615.67
UN Troops	18,353	534.76	718.00	0	148.81	594.62	6,374.00
UN Police	18,353	64.29	166.58	0	3.11	49.40	1,715.89
UN Observers	18,353	14.12	23.36	0	1.67	13.84	198.17
Prio Grid	389,955						

RADPKO contains geospatially and temporally disaggregated data down to a more granular level

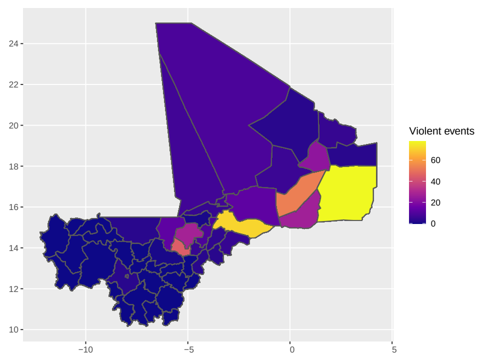
20. 646



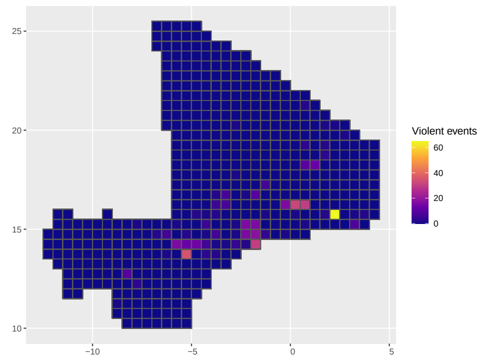
(a) Mali PKs by 2nd-order admin level



(b) Mali PKs by PRIO-grid



(c) Mali Violent events by 2nd-order admin level



(d) Mali Violent events by PRIO-grid

Figure 1: A visualization of peacekeepers (PKs) and violence in Mali, sorted by 2nd-order administrative units and PRIO-grids.

than ever before available to researchers.[21] By going through archival data available from the UN Department of Peace Operations (DPO), the dataset was constructed at an incredibly fine-grained level, especially when compared to the existing literature. RADPKO also disaggregates the PKO by gender and peacekeeper type, thus allowing for a more thorough analysis while controlling for variables that previous researchers have established affect peacekeeper effectiveness.[22]

Another significant benefit of using the RADPKO data is that all of the data is provided only for PKOs with a Chapter VII mandate. In this sense, each PKO in the RADPKO dataset has the authority and mandate to patrol locally and protect civilians. While not inherently the only type of peacekeeping mission that matters, the assumption that peacekeepers stop violence where it happens and the assumption that they respond to violence temporally require the PKO to have the ability to respond to local-level monthly violence without UNSC approval. Without a Chapter VII mandate, PKs have their hands tied and thus have little incentive or ability to respond to violence. For those reasons, among others, this research uses the RADPKO dataset to examine PK movement throughout the missions with a Chapter VII mandate. RADPKO covers PKO movement when deployed in the following countries: Sierra Leone, the Democratic Republic of Congo, Liberia, Côte d'Ivoire, Burundi, Sudan, South Sudan, Abyei,[23] Chad, Mali, and the Central African Republic.

Finally, this data improves researchers' capacity to analyze how peacekeepers effectively protect civilians. Because this data covers all Chapter VII missions, we have the entire universe of cases available to analyze. In other words, this sample is not truncated and gives us the most significant number of observations possible to answer the research question and test the hypotheses.

3.2 Various Models & Methods

Broadly, this paper seeks to answer the question: when and where do PKs reduce the amount of violence against civilians? To understand what that means, let us first take a step back and examine how violence against civilians is measured. I quantify violence against civilians in two distinct ways. First, I measure the violent events that occur, coded in ACLED's data as "Violence Against Civilians."[24]. Depending on the analysis used, this is often quantified as the number of violent events civilians receive in a given month and, in other instances, whether a violent event received by civilians occurred in a month. Second, I measure the number of deaths by civilians from violent means. This is quantified the same way as the violent events data, sometimes calculating the total number of deaths in a grid and sometimes calculating whether a civilian died by violent means.

Measuring deaths correctly also requires the correct model. While OLS models often assume that

21. Hunnicutt and Nomikos 2020.

22. For example, Narang and Liu 2021 show that peacekeeper gender has a substantively significant effect on the efficacy of peacekeepers

23. While not an independent country, RADPKO classifies it as such due to the region having a unique peacekeeping mission deployed.

24. Raleigh et al. 2010.

the dependent variable can take the value of any real number, that assumption is not as valid with violence data, especially considering violent events and deaths cannot be a fraction or go below zero. To remedy this, some scholars, and many in this literature, utilize a negative binomial count model. Negative binomial count models improve the measurement of count data. While this model is the most naive in my analysis, I employ it as a robustness check. Since other prominent pieces of the peacekeeping literature use it to measure violence against civilians, I replicate that analysis.

To understand peacekeepers' effect on violence against civilians, I employ several innovative methods in the causal inference literature. These methods represent significant advances over the prior peacekeeping effectiveness literature, with a specific focus on improving the accuracy of causal claims made on peacekeeping reduction of violence against civilians. For example, researchers often use matching between observations with bigger datasets to improve the leverage of causal claims. Matching entails examining individual observations that received the "treatment" (i.e., peacekeeper presence) and those that did not. Other papers in the literature use greedy matching with one-to-one replacement; however, propensity score matching can only account for observable covariates. These stakes are elevated because peacekeeping missions occur in environments that are not rich in data collection and availability, which further increases the chance of unobserved sorting occurring in the background that could bias the results. My analysis mitigates these issues by instead employing cardinality matching, which, among other benefits, improves the sensitivity test used to determine how biased the results are.[25] Matching sensitivity tests look "for the existence of unmeasured covariates that might bias the comparison between groups."[26] Thus, having an improved sensitivity test for potential missing data while simultaneously avoiding the pitfalls of propensity score matching means we can create a more balanced sample to run the analysis.

Furthermore, I exploit variation in mission deployment to interrogate the causal claims across country and time. While all of the missions in this dataset are chapter VII missions, that is where many of the similarities end. Missions vary on several factors, including but not limited to composition, duration, funding, and other forms of external support. Furthermore, the states peacekeepers deploy to are not uniform and vary on factors that could influence mission success or failure. For example, various country-level factors can include something as innocuous as the weather. If one country is experiencing a prolonged severe weather event, that could influence factors that directly affect violence against civilians. To control for this variation, I employ a multilevel model that matches units at the grid and country levels. Multilevel models are great for nested data designs since they "handle random effects, including the effects of grouping of observations under higher entities."[27] Essentially, these models group error terms at different levels of estimation, showing how confident we are that the regression model has

25. Visconti and Zubizarreta 2018.
26. Carreras, Vera, and Visconti 2022: 12.
27. Garson 2013.

handled possible confounding variables.

3.3 Dependent Variables

My dependent variable (DV) of *violence* is measured in two ways to capture as much variation in the data as possible. ACLED captures as many locations of violence and classifies the type of violence through various sources. I created a dummy variable *event* coded as equal to one for every row in ACLED's data, thus creating a measurement tool to see how often violence occurs. I then aggregated the number of events and deaths per grid cell per month.

So, my analysis models the dependent variable of violence in two ways: violent events and deaths, ran in a separate model. The models further disaggregate the violence by actor; previous research predicts a difference in peacekeeper reduction of violence from different actors.

Fjelde, Hultman, and Nilsson 2019 argue that expecting PKs to reduce every instance of violence against civilians is too hard of a test; yet, I note that peacekeepers in these missions are given an explicit mandate to protect civilians and respond to local violence escalation. The Security Council tasks them to respond geospatially and temporally to violence, so it is crucial to test whether they do that successfully. Further, analyses of PK effectiveness at reducing violence should be hard tests. They must test what peacekeepers are mandated to do to understand how effective they are.

3.4 Independent Variables

The independent variables (IVs) of interest come from the RADPKO dataset. *Deployed PKs* measure the number of peacekeepers in a grid, while *UN Troops*, *UN Police*, and *UN Observers* disaggregate the type of peacekeeper unit deployed. RADPKO measures the number of peacekeepers in a grid by the average over a month, which is why all versions of PK measurement are measured as a continuous and not a count variable.

Hunnicutt and Nomikos' RADPKO also disaggregates the PK data by gender, something not offered by any other existing dataset on peacekeeping deployments.[28] Narang and Liu 2021 find that the proportion of women in peacekeeping missions has direct effects on the effectiveness of peacekeeping missions, from more implementation of women's rights provisions to more reported instances of sexual violence. So, I control for the gendered breakdown of peacekeepers to account for this potential confounder. I included the number of female troops coded the same as the non-gendered breakdown but with "*f_*" preceding the variable name.

I further control for covariates that exist in the civil war and peacekeeping literature[29] and those that will plausibly affect the ability of peacekeepers to protect civilians from violence. I control for the

28. Hunnicutt and Nomikos 2020.
29. Fjelde, Hultman, and Nilsson 2019.

amount of urban area in a grid under *urban_gc* as a proxy for urban environments since peacekeepers will have more physical objects to navigate around and patrol in more dense urban areas. Similarly, I account for population density under *pop.dens*, as a greater number of civilians will result in more people for peacekeepers to protect. Furthermore, my regressions control for nighttime lights as a proxy of economic activity (*nlights_calib_mean*), the amount of mountainous terrain as a proxy of navigation difficulty (*mountains_mean*), the number of people per grid and population density as a measure of the number of people peacekeepers have to protect and how close they are (*pop_gpw_sum* & *pop.dens*), and finally the travel time to the nearest city as a proxy for road and infrastructure conditions that could slow mechanized peacekeeping units (*ttime_mean*). All control variables are aggregated at the grid-month level, with missing values imputed with the average from all other instances of the variable, a common practice in the methods literature.

4 Analysis/Discussion

4.1 Deaths as the DV

Broadly, the various models showed several important takeaways in assessing UN PKO violence reduction success. An important conclusion, and one that mirrors Fjelde, Hultman, and Nilsson 2019, is that peacekeepers never have a significant effect on reducing intentional government civilian killings. In a way, this is not surprising. Besides other prominent studies arriving at similar conclusions, it is plausible that peacekeepers would be unlikely to stop governments from killing their people. It is also very possible that the inability to stop government killings happens because governments redirect peacekeeper movement away from areas where they have a chance of killing civilians or because peacekeepers are reluctant to stop mass killings from the party in power, such as during the Rwandan genocide.

Regarding peacekeepers' ability to protect civilians from rebel killings, most models show little to no statistical or substantive effect. This result indicates that peacekeepers may not raise the costs of targeting civilians as much as previous research would indicate. However, an interesting puzzle does emerge from these results: when breaking the DV down into a binary outcome, peacekeepers have an effect of roughly zero, meaning they likely do not influence the data either way. Nevertheless, peacekeepers have a substantive and significant effect when breaking the DV into a continuous variable measuring the total number of deaths that occurred. These seemingly contradictory results spell out that peacekeepers do not affect or prevent violence outbreaks, but they affect the number of civilians killed when violence occurs.

Table 3: Matched MLM Results Binary Outcome

	Dependent variable:			
	Violent Event from Gov.	Death from Gov.	Violent Event from Reb.	Death from Reb.
	(1)	(2)	(3)	(4)
PK Units Deployed	-0.010^{***}	-0.001	0.003^{**}	0.007^{***}
	(0.002)	(0.001)	(0.002)	(0.001)
PK Military Troops Deployed	0.0001^{***}	0.00003^{***}	0.00003^{***}	0.00001^{**}
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
PK Police Deployed	-0.0001^{**}	-0.0001^{***}	-0.00003	-0.00002
	(0.00004)	(0.00003)	(0.00003)	(0.00003)
PK Observers Deployed	0.00001	-0.001^{***}	-0.0001	-0.001^{***}
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Female PK Troops	0.001^{***}	-0.001^{***}	0.00000	-0.0005^{**}
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Female PK Police	-0.001^{**}	0.001^{**}	-0.001^{**}	-0.0002
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Female PK Observers	0.030^{***}	0.015^{***}	0.005	0.004
	(0.007)	(0.005)	(0.006)	(0.005)
Avg. Mountain	0.084^{***}	0.056^{***}	0.060^{***}	0.045^{***}
	(0.010)	(0.007)	(0.008)	(0.007)
Travel Time to City	-0.0001^{***}	-0.0001^{***}	-0.00005^{***}	-0.00005^{***}
	(0.00002)	(0.00001)	(0.00002)	(0.00001)
Percent Urban	0.043^{***}		0.022^{***}	
	(0.004)		(0.003)	
Avg. Night Lights	-0.760^{***}		-0.499^{***}	
	(0.132)		(0.113)	
Sum Population	0.00000^{***}	0.00000^{***}	0.00000^{*}	0.00000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Population Density	-0.00005	-0.00000	-0.0001^{***}	-0.00004^{*}
	(0.00003)	(0.00002)	(0.00003)	(0.00002)
Constant	0.054^{***}	0.016^{**}	0.049^{***}	0.018
	(0.012)	(0.008)	(0.013)	(0.015)
Observations	5,072	5,072	5,072	5,072
Log Likelihood	1,539.749	2,946.330	2,407.789	3,357.385
Akaike Inf. Crit.	-3,047.498	-5,864.661	-4,783.578	-6,686.771
Bayesian Inf. Crit.	-2,942.994	-5,773.220	-4,679.074	-6,595.330
Note:				*p<0.1; **p<0.05; ***p<0.01

4.2 Violent Events as the DV

An incredibly interesting but seemingly contradictory conclusion also arises from the models: peacekeepers consistently prevent violence against civilians from governments in models measuring the DV as violent events rather than intentional killings. In other words, peacekeepers seem to prevent governments from attacking civilians generally but cannot protect them when the government goes so far as to employ violence severe enough to kill civilians.

In some ways, this aligns with other research stating that peacekeepers significantly affect the occurrence of nonviolent protests (Belgioioso, Salvatore, and Pinckney 2021). Belgioioso, Salvatore, and Pinckney 2021 argue that peacekeepers encourage nonviolent protest through norm diffusion, but this research indicates that the mere presence of peacekeepers likely raises the costs of harming civilians by government actors, thus providing a different possible mechanism: deterrence. Essentially, peacekeepers do save civilians, but any leader can defy that if they see the costs of peacekeeping condemnation as lower than the potential benefits. In other words, peacekeepers raise the costs of attacking civilians high enough that regular violent events go down in peacekeeper presence, while any government does not seem to be stopped after getting to the point that they start intentional civilian killings.

Looking at violent rebel attacks on civilians, the models show that peacekeepers are rarely shown to have any statistically significant effect. Indeed, the only matched model that shows a statistically significant connection is the multilevel matched model (table 3). Even so, the point estimate indicates a minimal real-world effect, which is close enough to zero to be treated as such. Thus, peacekeepers have little real-world effect when examining violent rebel events on civilians. This could be explained by the fact that rebels often use insurgent or guerilla tactics to fight (Hinkkainen Elliott, Polo, and Reyes 2021).

4.3 Re-testing Fjelde et al.'s (2019) Model

Finally, I check my models against Fjelde, Hultman, and Nilsson 2019 by running the same model they run with a dichotomous dependent variable of 5+ deaths, resulting in the matched sample analysis in Table 8. This model matches what Fjelde et al. ran, yet interestingly, I end up with different results. While I use the same regression model as Fjelde et al., a negative binomial logit model, this model differs from theirs in three specific ways that could explain the different outcomes. First, my dataset comprises a significantly higher number of observations. Fjelde et al. constructed their data from the UN archives, comprising the years 2000-2011, whereas I used the RADPKO dataset from Hunnicutt and Nomikos to map peacekeeper movement, which contains data from 1999-2018; this shows a possible time-variance bias present. In other words, the years 1999 and 2012-2018 could be influencing the outcome, indicating that something in peacekeeping missions may have fundamentally shifted during those years. Second, my model uses cardinality rather than propensity score matching. It is possible that the propensity score matching biased the results (King and Nielsen 2019). Finally, my violence data comes from a dataset that measures violence from different sources. It is possible that the UCDP's likely undercounting of violence data[30] biased the estimates higher than they would have otherwise shown.

5 Conclusion

This paper contributes to the peacekeeping literature by improving upon the research design, data, and methods of scholars past. Fjelde, Hultman, and Nilsson 2019 began the necessary work on disaggregating peacekeeping and violence data to a sub-national level. However, as noted by Walter, Howard, and Fortna 2021 and now this paper, future researchers must build upon the peacekeeping effectiveness literature. Now that we know peacekeeping works at the country level to protect civilians (Hultman, Kathman, and Shannon 2013, 2014; Bara and Hultman 2020), this research paper sought to answer an important question: where does peacekeeping work, and who does it work against? Broadly, this paper agrees with some of the conclusions of Fjelde, Hultman, and Nilsson 2019, such as peacekeepers not preventing intentional government killings while also disputing whether peacekeepers prevent violence from rebel actors. Future research should dig deeper into the data at a country-level to understand what causes peacekeepers to reduce violence against civilians.

With these results partially contradicting Fjelde, Hultman, and Nilsson 2019, further analysis should be done to examine why. For example, it is possible that the multilevel model correctly accounted for the variation in country-level factors, something the more naive binary logit would have had trouble differentiating. That seems to be the most likely solution, but other potential reasons remain, such as the use of a different matching process to pre-treat the data or the fact that the data in my sample covering the same countries but almost twice as many years of analysis, changed the outcome.

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30. Eck 2012.

Table 4: Pre-matched Negative Binomial Logit Results (binary outcome)

	Dependent variable:			
	Violent Event from Gov.	Death from Gov.	Violent Event from Reb.	Death from Reb.
	(1)	(2)	(3)	(4)
PK Units Deployed	-0.134^{***}	-0.020	0.058^{*}	0.109^{**}
	(0.036)	(0.049)	(0.035)	(0.045)
PK Military Troops Deployed	0.001^{***}	0.001^{***}	0.0002	0.001
	(0.0002)	(0.0003)	(0.0003)	(0.0004)
PK Police Deployed	0.0002	-0.009^{**}	0.0004	0.002
	(0.001)	(0.004)	(0.001)	(0.002)
PK Observers Deployed	-0.001	-0.032^{***}	0.007	-0.024^{**}
	(0.006)	(0.011)	(0.007)	(0.012)
Female PK Troops	0.016^{***}	-0.006	0.004	-0.003
	(0.006)	(0.013)	(0.011)	(0.014)
Female PK Police	0.003	0.055^{**}	-0.026	-0.014
	(0.008)	(0.023)	(0.017)	(0.018)
Female PK Observers	-0.079	0.245	-0.106	0.010
	(0.132)	(0.229)	(0.224)	(0.292)
Avg. Mountain	2.253^{***}	2.448^{***}	2.026^{***}	2.004^{***}
	(0.178)	(0.214)	(0.184)	(0.214)
Travel Time to City	-0.004^{***}	-0.005^{***}	-0.003^{***}	-0.002^{***}
	(0.0004)	(0.001)	(0.0003)	(0.0004)
Percent Urban	0.652^{***}		0.298^{***}	
	(0.067)		(0.078)	
Avg. Night Lights	-14.708^{***}		3.022	
	(3.157)		(2.681)	
Sum Population	0.00000^{*}	0.00000	0.00000	0.00000^{*}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Population Density	0.0001	0.002^{**}	-0.001	-0.003
	(0.001)	(0.001)	(0.001)	(0.002)
Constant	-3.668^{***}	-4.760^{***}	-4.658^{***}	-5.140^{***}
	(0.202)	(0.208)	(0.189)	(0.167)
Observations	65,557	65,557	65,557	65,557
Log Likelihood	-1,705.974	-1,065.842	-1,906.615	-1,330.016
θ	61.723 (47.753)	23.295 (23.239)	65.780 (76.546)	56.663 (73.739)
Akaike Inf. Crit.	3,439.948	2,155.684	3,841.230	2,684.033

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: Matched Negative Binomial Logit Results (binary outcome)

	Dependent variable:			
	Violent Event from Gov.	Death from Gov.	Violent Event from Reb.	Death from Reb.
	(1)	(2)	(3)	(4)
PK Units Deployed	-0.170^{***}	-0.079	-0.024	0.085^{*}
	(0.040)	(0.053)	(0.036)	(0.044)
PK Military Troops Deployed	0.001^{***}	0.001^{***}	0.0002	0.0002
	(0.0002)	(0.0003)	(0.0003)	(0.0004)
PK Police Deployed	0.0003	-0.008^{**}	0.002	0.002
	(0.001)	(0.004)	(0.001)	(0.002)
PK Observers Deployed	0.001	-0.026^{**}	0.009	-0.019^{*}
	(0.006)	(0.011)	(0.007)	(0.012)
Female PK Troops	0.013^{*}	-0.024	0.005	-0.013
	(0.007)	(0.015)	(0.013)	(0.015)
Female PK Police	-0.002	0.043^{**}	-0.038^{**}	-0.020
	(0.008)	(0.020)	(0.018)	(0.018)
Female PK Observers	0.026	0.480^{*}	0.074	0.200
	(0.137)	(0.246)	(0.285)	(0.303)
Avg. Mountain	1.558^{***}	2.167^{***}	1.924^{***}	2.770^{***}
	(0.257)	(0.292)	(0.325)	(0.337)
Travel Time to City	-0.003^{***}	-0.006^{***}	-0.003^{***}	-0.006^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Percent Urban	0.675^{***}		0.795^{***}	
	(0.087)		(0.130)	
Avg. Night Lights	-20.533^{***}		-28.380^{***}	
	(4.544)		(6.115)	
Sum Population	0.00000^{**}	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Population Density	-0.001	-0.0003	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Constant	-2.627^{***}	-3.496^{***}	-2.515^{***}	-3.941^{***}
	(0.309)	(0.337)	(0.386)	(0.379)
Observations	5,072	5,072	5,072	5,072
Log Likelihood	-629.767	-402.939	-468.555	-345.020
θ	492.546 (1,077.867)	250.361 (688.438)	305.190 (632.775)	207.628 (469.471)
Akaike Inf. Crit.	1,287.534	829.879	965.110	714.039
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6: Matched MLM Results Continuous Outcome

	Dependent variable:			
	Violent Event from Gov.	Death from Gov.	Violent Event from Reb.	Death from Reb.
	(1)	(2)	(3)	(4)
PK Units Deployed	-0.017^{***}	-0.056	0.006	0.345^{***}
	(0.004)	(0.054)	(0.004)	(0.067)
PK Military Troops Deployed	0.0001^{***}	0.0003	0.0001^{**}	0.0004
	(0.00002)	(0.0003)	(0.00002)	(0.0004)
PK Police Deployed	-0.00004	-0.0004	-0.0001	-0.003^{**}
	(0.0001)	(0.001)	(0.0001)	(0.001)
PK Observers Deployed	-0.0001	-0.015^{*}	-0.001^{*}	-0.036^{***}
	(0.001)	(0.009)	(0.001)	(0.010)
Female PK Troops	0.001^{*}	-0.013	0.0003	-0.008
	(0.001)	(0.010)	(0.001)	(0.012)
Female PK Police	-0.002^{*}	0.016	-0.002^{*}	0.015
	(0.001)	(0.011)	(0.001)	(0.013)
Female PK Observers	0.033^{**}	0.257	0.018	-0.162
	(0.016)	(0.210)	(0.015)	(0.253)
Avg. Mountain	0.090^{***}	0.850^{***}	0.114^{***}	1.369^{***}
	(0.022)	(0.272)	(0.021)	(0.335)
Travel Time to City	-0.0001^{***}	-0.001^{**}	-0.0001^{***}	-0.001
	(0.00004)	(0.001)	(0.00004)	(0.001)
Percent Urban	0.089^{***}		0.045^{***}	
	(0.008)		(0.008)	
Avg. Night Lights	-1.836^{***}		-0.808^{***}	
	(0.291)		(0.283)	
Sum Population	-0.00000	0.00000	0.00000^{**}	0.00000^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Population Density	0.0001^{**}	0.001	-0.0002^{***}	-0.002^{**}
	(0.0001)	(0.001)	(0.0001)	(0.001)
Constant	0.145^{***}	0.458^{**}	0.087^{***}	-0.102
	(0.024)	(0.197)	(0.023)	(0.257)
Observations	5,072	5,072	5,072	5,072
Log Likelihood	-2,470.810	-15,713.740	-2,348.214	-16,615.310
Akaike Inf. Crit.	4,973.620	31,455.490	4,728.427	33,258.630
Bayesian Inf. Crit.	5,078.123	31,546.930	4,832.931	33,350.070
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7: Pre-matched Results (Binary outcome of 5 or more deaths & events)

	Dependent variable:		
	Violent Event from Gov.	Death from Gov.	Deat from Reb
	(1)	(2)	(3)
PK Units Deployed	5.701	0.113	0.097
	(7.531)	(0.123)	(0.061)
PK Military Troops Deployed	−0.023	−0.0002	0.0004
	(0.047)	(0.001)	(0.0005)
PK Police Deployed	0.098	−0.003	−0.012
	(0.140)	(0.004)	(0.016)
PK Observers Deployed	−1.774	−0.029	−0.012
	(1.832)	(0.024)	(0.016)
Female PK Troops	−3.479	−0.041	0.032
	(46.141)	(0.059)	(0.023)
Female PK Police	0.480	0.047^{*}	−0.308
	(2.451)	(0.028)	(0.390)
Female PK Observers	−448.690	0.009	−0.248
	(1, 280, 651.000)	(0.499)	(0.588)
Avg. Mountain	1.574	2.162^{***}	2.191^{***}
	(3.497)	(0.343)	(0.279)
Travel Time to City	−0.003	-0.005^{***}	-0.003^{***}
	(0.006)	(0.001)	(0.001)
Percent Urban	4.126		
	(3.310)		
Avg. Night Lights	−261.381		
	(178.047)		
Sum Population	0.00001	−0.00000	0.00000
	(0.00001)	(0.00000)	(0.00000)
Population Density	0.018	0.003^{***}	−0.00004
	(0.018)	(0.001)	(0.002)
Constant	−1.113	-5.429^{***}	-5.627^{***}
	(5.672)	(0.302)	(0.235)
Observations	65,557	65,557	65,557
Log Likelihood	-101.358	-550.206	-781.803
θ	0.0002^{***}(0.00003)	12.988 (29.044)	20.165 (30.279)
Akaike Inf. Crit.	230.717	1,124.412	1,587.605
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 8: Matched Results (Binary outcome of 5 or more deaths)

	Dependent variable:	
	Death from Gov.	Death from Reb.
	(1)	(2)
PK Units Deployed	0.028	0.061
	(0.130)	(0.062)
PK Military Troops Deployed	−0.0002	−0.00001
	(0.001)	(0.0005)
PK Police Deployed	−0.002	−0.015
	(0.004)	(0.017)
PK Observers Deployed	−0.026	−0.0002
	(0.025)	(0.016)
Female PK Troops	−0.067	0.023
	(0.065)	(0.024)
Female PK Police	0.041	−0.280
	(0.028)	(0.375)
Female PK Observers	0.108	0.013
	(0.541)	(0.615)
Avg. Mountain	1.796^{***}	3.182^{***}
	(0.489)	(0.502)
Travel Time to City	-0.005^{**}	-0.012^{***}
	(0.002)	(0.003)
Sum Population	−0.00000	−0.00000
	(0.00000)	(0.00000)
Population Density	0.002^{*}	0.001
	(0.001)	(0.002)
Constant	-4.308^{***}	-3.508^{***}
	(0.522)	(0.590)
Observations	5,072	5,072
Log Likelihood	-191.317	-184.606
θ	78.406 (392.242)	45.779 (80.635)
Akaike Inf. Crit.	406.634	393.211
Note:		*p<0.1; **p<0.05; ***p<0.01

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