**Community exposure to violent conflict increases the risk of recent intimate partner violence in Rwanda**

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**Introduction**

Gender-based violence (GBV) takes place in every country in the world, causing disability and death to an untold number of individuals every day. Intimate Partner Violence (IPV) is the most common form of GBV, meaning that most survivors of GBV know their perpetrators. While men are affected by GBV, the vast majority of survivors of GBV are women (1). The recent global focus on GBV is based on an extensive body of research conducted in the last decade that has documented the prevalence in over 90 countries. These studies have also examined risk factors for IPV and have described its devastating impact on affected individuals and the communities in which they live (2). Prevalence estimates of recent IPV, defined as IPV within the past year, and based on data from 81 countries, show a great deal of variability around the world, ranging from 16% of ever-partnered women in East Asia to 65% in central Sub-Saharan Africa (3). Estimates of IPV prevalence in complex emergency settings are even higher, with reported levels of up to 80% of women. Other forms of GBV, such as stranger rape, were less commonly reported than IPV, even in emergency situations (4).

While studies have explored the general characteristics that put women at risk of IPV, less work has been done on community factors. The positive association of a community's accepting attitudes of wife-beating and the prevalence of IPV have been documented (5). However, other community characteristics that may help target interventions and response have not been explored. For example, in the context of intervention planning, it is useful to know about the geographic variability of risk, and what may be driving it. Here we undertake an investigation of these phenomena given by two questions: 1) Does risk of recent IPV cluster geographically after controlling for known risk factors (e.g. economic and educational status, community-level acceptance of IPV), and 2) Does exposure to long-term violent conflict increase risk of recent IPV?

**Data and Methods**

To answer these two questions, this study utilizes data from Rwanda's 2010 Demographic and Health Survey (DHS) and the Armed Conflict and Location of Event Dataset (ACLED)(6). The ACLED provides data on the date, location, and characteristics of violent incidents across Africa and elsewhere since 1997. The DHS provided the data for the study population, which consisted of ever-married women between the ages of 15 and 49 who were selected for the domestic violence module. This yielded a sample of 3,468 respondents. Recent IPV was defined as any single positive response to a set of questions about physical or sexual violence, or threat of physical harm, that took place in the previous 12 months. The survey was based on a probability-sampling protocol enabling generalization back to married women of reproductive age in Rwanda and each of its provinces. To derive a measure of exposure to violent conflict from ACLED, we calculated the mean number of conflict days per year within 50 kilometers of each of the 492 DHS clusters. The time period over which this exposure was measured was the five years

leading up to the 2010 DHS. A violent conflict was defined as any kind of battle (such as between rebel groups or government forces) or violence against civilians.

To test the degree to which IPV clusters geographically, and whether exposure to violent conflict affects risk of IPV, the analysis proceeded in two stages. First, a model-based cluster analysis was conducted to determine whether or not risk of domestic violence clusters geographically after controlling for known risk factors such as education, wealth, age, and community acceptance of IPV, which was measured as the proportion of respondents in each survey site who had a positive response to a set of five questions about justification of domestic violence. This analysis was done by calculating the Getis-Ord Local Gi test statistic on the standardized random effect of a Bayesian generalized mixed effects model of IPV on the covariates. The Getis-Ord Local Gi test scans a study area and compares each observed value with neighboring values and then produces a z-score and corresponding p-value that determines the extent to which areas with high or low values cluster geographically. In this case, the Getis-Ord Local Gi scanned across the study area and tested the degree of similarity between the random effects at each sample cluster and those of neighboring clusters, with statistically significant high values indicating those areas where risk of IPV remained high even after controlling for known risk factors. For this test, a scan radius of 50 kilometers was used in conjunction with an inverse distance band specification, meaning that clusters outside the 50 kilometer radius at each point in the spatial scan did not influence the calculation of the test statistic. This choice was made because it corresponded to the choice of a 50 kilometer radius over which violent conflict is hypothesized to have a significant effect on risk of recent IPV.

The second stage of the analysis proceeded in a similar manner to the first. In this case, however, the violent conflict exposure was added to the regression model, which allowed us to 1) test the hypothesis that exposure to violent conflict is associated with an increased risk of IPV, and 2) determine the extent to which controlling for exposure to violent conflict alters the geographic clustering of IPV risk. To ensure comparability of results across stages, the same model specifications for the first stage of the analysis were applied to the second stage. Both regression analyses and cluster analyses were carried out in R version 3.0.2.

**Results**

Results from the first regression model show that increased socioeconomic status, education, and age had significant, protective effects on risk of recent IPV, while higher community-level acceptance of recent IPV significantly increased an individual's risk. However, despite controlling for these known risk factors, the first cluster analysis shows a high degree of unexplained IPV risk along Rwanda's northwestern border areas, particularly the border with the Democratic Republic of Congo (DRC) and in the south along the border with Burundi (see Figure 1).

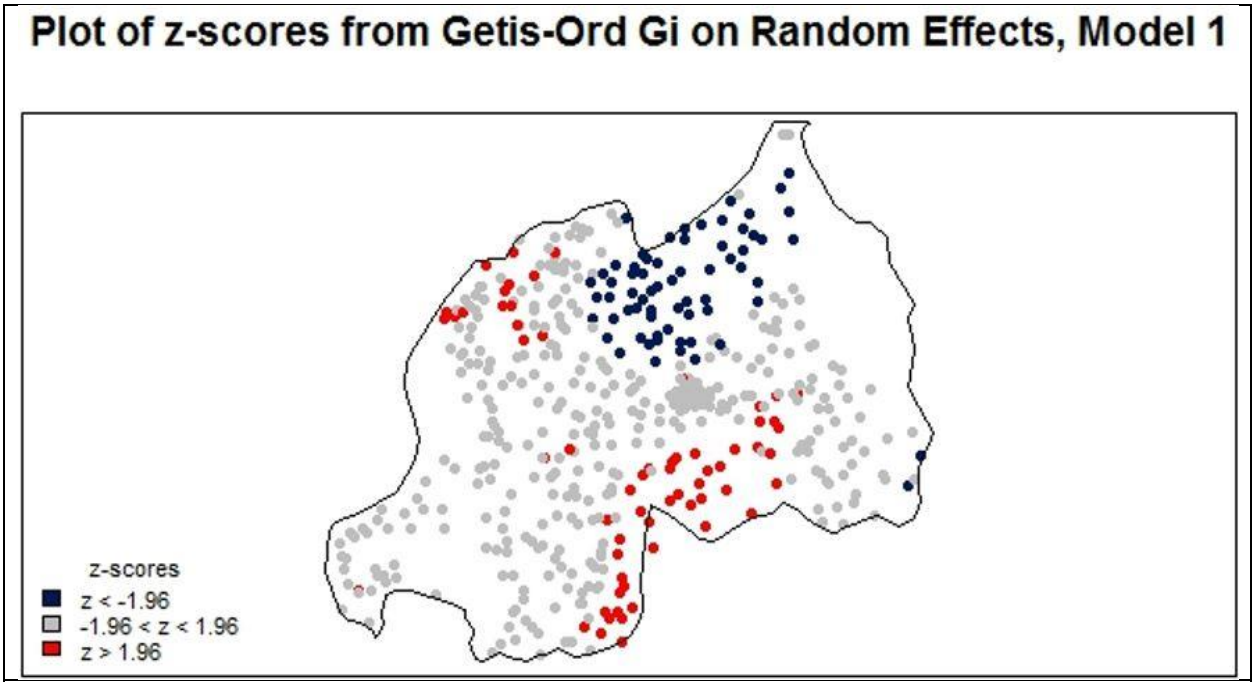


**Figure 1**: Geographic cluster analysis showing areas of high and low unexplained risk. Red areas indicate significantly high unexplained risk (z-score > 1.96); Blue areas indicate significantly low unexplained risk (z-score < -1.96).

We interpret the spatial pattern of high unexplained risk as an indication that there were missing risk factors from the model, and we hypothesize that prolonged exposure to violent conflict increases an individual's risk of recent IPV. The second model confirms this, as exposure to violent conflict demonstrated a statistically significant, positive association with the odds of reporting recent IPV, with an increase of 1 violent conflict per year corresponding to a 1.1S% increase in the odds of reporting recent IPV (OR 1.011, 95% CrI 1.005 – 1.017). See table 1 for results from both models. Further support of this hypothesis can be found by way of the second cluster analysis on the standardized random effect of the model, in which we find a considerable recession of high clustering across the border with the DRC (see Figure 2). Interestingly, there still remains considerable high clustering along Rwanda's southern border with the Burundi, and low clustering along the northern border with Uganda. In this case, we believe the clustering pattern is potentially the result of other risk factors we were unable to control for, as well as spatial autocorrelation resulting from the DHS sampling design.

**Table 1: Bayesian GLMM results**

| | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| **Variable** | **Odds Ratio** | **Lower CrI** | **Upper CrI** | **Odds Ratio** | **Lower CrI** | **Upper CrI** |
| Age (single years) | 0.986 | 0.977 | 0.995 | 0.987 | 0.978 | 0.996 |
| Education (no education is reference) | | | | | | |
| Primary | 1.292 | 1.077 | 1.552 | 1.3131 | 1.094 | 1.577 |
| Secondary | 1.325 | 0.965 | 1.819 | 1.337 | 0.974 | 1.835 |
| Higher | 1.221 | 0.546 | 2.619 | 1.21 | 0.542 | 2.592 |
| Wealth quintiles (lowest is reference) | | | | | | |
| 2nd quintile | 0.948 | 0.766 | 1.171 | 0.944 | 0.764 | 1.167 |
| Middle quintile | 1.054 | 0.849 | 1.310 | 1.049 | 0.845 | 1.304 |
| 4th quintile | 0.95 | 0.761 | 1.186 | 0.957 | 0.767 | 1.195 |
| Highest quintile | 0.685 | 0.527 | 0.891 | 0.672 | 0.517 | 0.874 |
| Community acceptance of IPV (%) | 1.013 | 1.008 | 1.018 | 1.009 | 1.004 | 1.015 |
| Community exposure to conflicts (conflict days/year) | NA | NA | NA | 1.011 | 1.005 | 1.017 |
| n = 3468 | | | | | | |
| DIC | 4677 | | | 4669 | | |

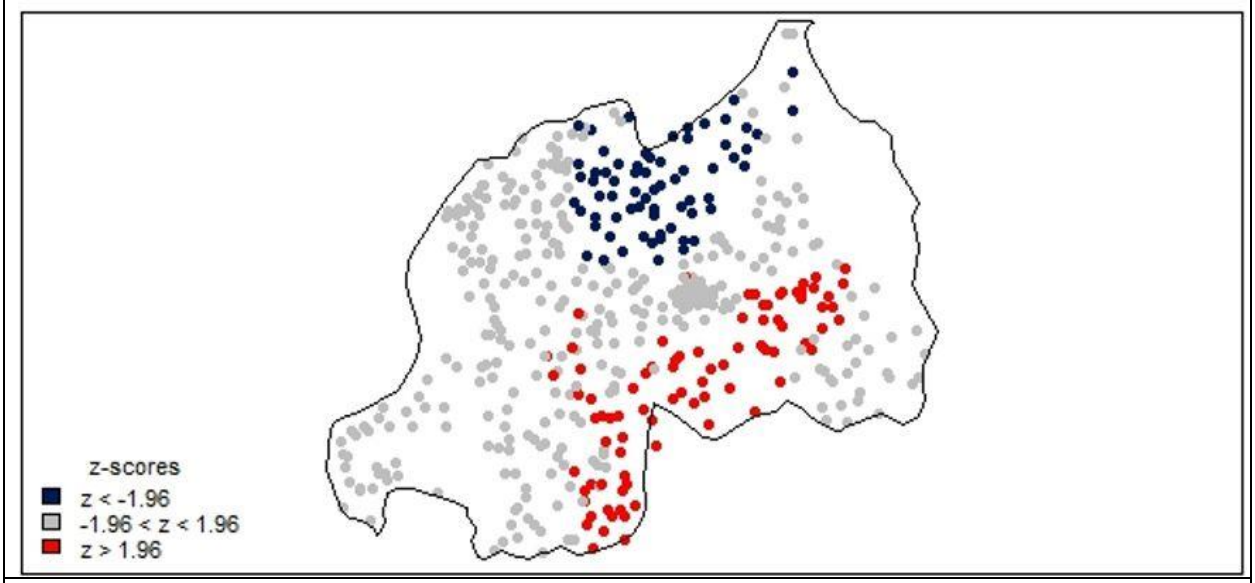


**Figure 2**: Geographic cluster analysis showing areas of high and low unexplained risk after controlling for violent conflict exposure. Red areas indicate significantly high unexplained risk (z-score > 1.96); Blue areas indicate significantly low unexplained risk (z-score < -1.96).

**Discussion**

To our knowledge, this is the first study to investigate either the subnational spatial distribution of IPV risk or the effect of violent conflict on risk of recent IPV. Our findings suggest that, after controlling for known risk factors, there are still areas of significantly high IPV risk, primarily along border areas. Further, our findings show that exposure to violent conflict is associated with a significant increase in recent IPV risk, and that accounting for this also addressed some of the unexplained risk observed in the cluster analysis (and resulted in a significant improvement in model fit). Both of these findings have implications for intervention efforts designed to reduce IPV in Rwanda and elsewhere, given that risk is not evenly distributed geographically, and given that an exposure not previously considered has now been demonstrated to be a significant risk factor.

That said, there are important limitations to this study. First, key risk factors such as HIV and spousal alcohol consumption could not be controlled for, nor could experience of violence in childhood. HIV has a bidirectional effect on IPV risk, with HIV positive individuals being at increased risk of IPV, while IPV in the form of sexual violence is itself a significant risk factor for HIV transmission. Because the DHS is a cross-sectional survey, we cannot assess this risk factor. Nor can we account for alcohol use or experience of violence in childhood since questions about these issues were not asked in the survey. Nevertheless, given the strong observed association between recent IPV and exposure to endemic violent conflict, and given the reduction in unexplained risk across a large geographic area, we believe these findings to be valid.

**Future directions**

This study used the 2010 cross-sectional DHS survey to investigate subnational geographic patterns of recent IPV risk and whether or not exposure to long-term violent conflict is a significant risk factor. For our violent conflict exposure we chose a duration of 5 years, which will allow us to begin assessing the effect of violent conflict on recent IPV longitudinally. Additionally, because the domestic violence module of DHS is regularly implemented across sub-Saharan Africa, our future work will incorporate data from other countries, which have experienced different levels and types of conflict. Thus, we hope to answer our two questions not just in Rwanda, but for sub-Saharan Africa in general.

Finally, it is important to note that much of this work is exploratory, and is our first look at the questions mentioned in the introduction. Indeed, while we interpret the observed geographic clustering as an indication of missing covariates that is partially dealt with by including a measure of violent conflict, one important consequence of residual geographic clustering is that it indicates that a key regression assumption—independence among observations—has been violated. Thus, future efforts will focus on constructing additional models to begin accounting for this lack of independence. An example of such a model would be mixed effects spatial models, which do not have analytic solutions and therefore require Bayesian approaches for inference. Such models can be easily implemented in R or WinBUGS.

**References**

1. Organization WH. WHO multi-country study on women's health and domestic violence against women: summary report of initial results on prevalence, health outcomes and women's responses. 2005.
2. Garcia-Moreno C, Watts C. Violence against women: an urgent public health priority. B World Health Organ. 2011;89(1):2-.
3. Devries KM, Mak JYT, Garcia-Moreno C, Petzold M, Child JC, Falder G, et al. The Global Prevalence of Intimate Partner Violence Against Women. Science. 2013;340(6140):1527-8.
4. Stark L, Ager A. A Systematic Review of Prevalence Studies of Gender-Based Violence in Complex Emergencies. Trauma Violence Abus. 2011;12(3):127-34.
5. Abramsky T, Watts CH, Garcia-Moreno C, Devries K, Kiss L, Ellsberg M, et al. What factors are associated with recent intimate partner violence? findings from the WHO multi-country study on women's health and domestic violence. BMC public health. 2011;11:109.
6. Raleigh C, Linke A, Hegre H, Karlsen J. Introducing acled: An armed conflict location and event dataset special data feature. Journal of peace Research. 2010;47(5):651-60.