A Clash of Generations or Regions?

Using Bayesian Multilevel Models to Estimate Youth Bulge Effects on Civil Conflict

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Submitted in partial fulfillment of the
requirements for the degree of
Master of Arts in Quantitative
Methods in the Social Sciences
under the Executive Committee
of the Graduate School of Arts and Sciences

COLUMBIA UNIVERSITY

2024

Introduction

Conflict is an ever-present aspect of human society. It shapes history, migration, art, politics and nations. We learn much of our history through the prism of wars, their consequences and how they change the world. Although a cursory glance at news headlines may not feel like it, as the world has moved into the 21st century it has experienced a marked decline in the amount of large-scale conflict, particularly conflict between nation-states. Large scale wars between countries occur far less often than they have in the past. However, that does not mean that all conflict has been resolved. Indeed, we still see many occurrences of conflict events, particularly conflicts referred to as "intrastate conflicts". These occur mainly within countries and tend to be attributed to grievances between citizens and governments, or between ethnic groups cohabitating within a country. And while these types of conflicts do not inflict quite the same world-spanning, devastating effects that are often seen with large-scale conflicts, intrastate conflict can still destabilize countries (as well as regions), uproot civilians and cause chaos within communities. Whenever a phenomenon such as this occurs, we inevitably seek to understand and, hopefully, explain it. Although we are not able to get into the mind of those who decide to initiate or participate in these conflict events, investigating the country-level factors that may put a nation-state at higher risk of conflict could help governmental organizations direct resources more effectively for preventing it in the future. This paper will examine the factors that put a country at higher risk of the occurrence of conflict, focusing in particular on how so-called 'youth bulges' (when there is a large cohort of the adult population aged 15-24) influence this risk. In the next section, I will build on previous research in the field to develop a model that predicts a country's probability of conflict occurrence in a given year based on nation-level political, geographical, and socioeconomic factors. The second section describes the methodology, including data, measures, and elicitation of the models. Prior research has focused on global-level analyses and so, after analyzing a similarly structured global-level model, I will utilize a multilevel framework to study these effects at a regional level. This framework allows for additional insight into how conflict predictors may vary, and gives context for why some predictors (with an emphasis on youth cohort aged 15-24) may be more complicated than prior research has indicated. This is followed by the presentation of the main results and discussion. In the concluding section, I will address possible implications of the findings and directions for further research. Based on this analysis, I will show that although various factors such as youth bulges play a role in the risk of a country's propensity toward intrastate conflict, these do not appear to be global-level associations. In fact, they have a lot to do with the region in which they occur. Taking these aspects into account will be important when planning initiatives that target these factors to help prevent conflict before it afflicts a particular country.

Literature Review

Although conflict among countries has been studied throughout history, as the world emerged from the Cold War and smaller, contained conflict events occurred in both established and newly-created countries, researchers attempted to understand the complex relationships between factors that could give rise to that type of violence. While specific causes can vary significantly from conflict to conflict, certain demographic, economic, political, and social conditions have been posited as increasing a country's risk of descending into civil strife. One factor that has garnered increased attention since the early 2000's is the phenomenon of "youth bulges" - countries with disproportionately large cohorts of young people, typically defined as those between the ages of 15-24. Researchers have theorized several pathways by which youth bulges might increase conflict risk:

1. Through a type of "labor market crisis" where educational systems and economies fail to absorb large youth cohorts into productive employment, leading to a mass of idle, frustrated young men prone to violence (Urdal, 2006).
2. From resource competition as growing youth populations strain food, water, land and other finite resources (Kahl, 2006).
3. Via an "institutional crowding" effect where youth bulges overburden weak political institutions and create pressures for rebellion (Goldstone, 2002).

While appealing in a theoretical framework, these pathways have been subjected to growing empirical scrutiny in recent years. It is possible that youth bulges alone are neither necessary nor sufficient for sparking civil conflict, but can amplify risks under certain conditions. Quantitative cross-national studies have found statistically significant correlations between countries with large youth population shares and increased incidence of civil conflict (Urdal, 2006; Collier & Hoeffler, 2008; Fearon & Laitin, 2003). However, the effects tend to be modest in size and sensitive to model specifications. Some studies fail to find any direct, independent effect of youth bulges on conflict onset once other structural factors like poverty, regime type, and ethnic fractionalization are controlled for (Yair & Miodownik, 2016).

Case study evidence also presents a nuanced picture. Some countries with very youthful age structures like Zambia, Botswana and Bangladesh have avoided major civil violence, while others like Sierra Leone, Liberia, and Afghanistan saw youth participation in brutal conflicts (Urdal & Hoelscher, 2009). The Middle East and North Africa region is often cited as a prime example of the "youth bulge and instability" effect, with the 2011 Arab Spring uprisings partly attributed to the region's unique demographic profile (LaGraffe, 2012). Yet even in this example, youth discontent led to mass protests and revolution in some states (e.g. Tunisia, Egypt) but not others (Morocco, Saudi Arabia).

Youth bulges may play more of a role as a conditioning factor that can catalyze conflicts in the presence of other socioeconomic variables. Some of the most important factors that have been identified are below:

Previous Conflict

Some research has shown that conflicts that appear to have come to an end are at high risk of recurring, around 40% by some estimates (Collier, Hoeffler and Söderbom 2008). Even when counties succeed in preserving peace beyond the first decade, they can enter a phase called “marginalized countries at peace”. This typically entails low incomes and lackluster economic growth along with distinctly higher risk of conflict compared to other countries (Collier 2007). Roughly one-sixth of post-conflict countries move to the group of “successful developers” with substantially reduced conflict risk (Collier et al. 2003). This “stickiness” makes sense, as there is often not a clear-cut ending to conflict that satisfies all parties. Grievances can remain, simmer, and easily boil over in a short time span.

Regional Influence

Conflicts tend to be clustered in a handful of geographic regions. Although this may be an effect of other risk factors (such as low economic growth) being geographically clustered as well, there can also be cross-border spill-over effects (Collier et al. 2003; Gleditsch 2007). Although the exact pathway that regional effects play needs to be studied further, regions of countries can have similar cultural, societal and geographic features that may play an important role in conflict risk.

Overall Population Level

Greater populations have been seen to be associated with increased conflict risks. Larger populations within a nation-state may strain resources and push populations into denser areas. These factors can contribute to rising tension that can spill over into conflict if grievances are not addressed. However, the increase in the risk of conflict doesn't appear to increase proportionally with total population size. In fact, some studies have indicated that the per-capita risk of civil war onset decreases with population size (Hegre et al. 2013).

Education

A more educated populace has been associated with lower conflict risk in many studies. Higher levels of primary enrollment, secondary male enrollment, greater education expenditure, and higher literacy levels have all been associated with lower conflict risk (Thyne 2006). Additionally, secondary male enrollment has been observed to be associated with lower risk of the onset of civil war (Collier and Hoeffler 2004) as well as with shorter wars (Collier et al. 2004). Education can allow citizens more pathways to address economic and societal grievances, as well as providing them new opportunities for income. The sunken cost of investing in education can also provide a greater barrier when assessing the risk of participating in conflict as there may be more to lose by participating.

Per-capita GDP

Many researchers have found per-capita GDP to be associated with a high risk of the onset of conflict, and this variable is included in most research on conflict risk (Hegre and Sambanis 2006). In theory, as incomes rise there is less incentive for individuals to take the risk of participating in conflict. Although a powerful variable on its own, country-level per-capita GDP can mask distributional inequalities within a country. For this reason, the variable is typically included with additional factors that capture other aspects of development.

Polity Regime

The polity of a country (the political organization or structure of a country) may also play a role in the propensity for conflict. There are a few possible pathways for this relationship to occur. In one sense, citizens in more autocratic regimes may face greater political oppression, which can aggravate grievances but also severely restrict their opportunities for demonstration, protest, and potential conflict. Citizens in democratic regimes may have more freedom to protest (which can escalate and lead to conflict), but also have different avenues to redress grievances beyond direct conflict (through voting, civil action, etc.). In fact, some studies have found a curvilinear or "inverted U" relationship, which implies that countries most at risk of conflict are those with a middle form of government that is neither strongly autocratic nor democratic (Hegre et al., 2001). This may be a "worst-case" scenario where there is neither alternative outlets for civil action nor a strong central government that keeps order, which may lead to conflict.

Infant Mortality Rate

Many recent studies have used infant mortality rate (IMR) as a developmental factor to complement typical measures of income such as GDP-per-capita. IMR appears to be strongly associated with an increased risk of armed conflict (Urdal 2005) and has been seen to have strong effects on state failure and conflict (Esty et al. 1998).

Data and Methods

In this paper, I utilize a large-N quantitative dataset using country-year as the unit of analysis. The data includes all sovereign states in the international system as well as dependent areas with an estimated total population of at least 150,000 in 1992. This work focuses on the time period of 1992-2018. The reason for this is that the world shifted significantly with the fall of the Soviet Union (USSR) and the end of the Cold War in the early 1990s. A host of new countries were created that had previously been under the umbrella of the USSR, and dynamics between large nation-states shifted. Much of the research on civil conflict in the early 2000s only had about a decade of modern (Post-Cold War) data to work with. We now have more than an additional decade to investigate and validate those previous results. The full dataset used in this analysis is comprised of 186 sovereign states or dependent areas, with a total of 5,022 observations.

Eight features were used to build this model. Due to the distributed nature of economic and socioeconomic data, these were gathered and combined to create the full dataset used in the analysis. Exact sources and structure of each source are detailed below.

Conflict Events

The model outcome is the occurrence of 1 or more conflict events in a given country-year. Data on domestic armed conflict events is drawn from the UCDP/PRIO Armed Conflict Dataset (Gleditsch et al. 2002, Davies et al. 2023). This data is compiled and published annually by the Department of Peace and Conflict Research at Uppsala University (Sweden) and is the global standard of how conflicts are systematically defined and studied. Armed conflict in this context is defined as “a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths in one calendar year" (Gleditsch et al. 2002). Focusing on the period 1992-2018, a total of 1,068 events (783 unique country-event-years) were identified. We can begin to get a sense of the distribution of the outcome by looking at the conflict rate for each region in Figure 1. Already, we see a right-skew of the distribution, with some regions having conflict rates in excess of 25% while others see rates below 10%. This will be explored further as I develop the multilevel model. To validate that the shape of this distribution was not specific to only the timeframe included in the analysis (1992-2018) I examined the distribution with a broader timeframe of 1970-2018. The distribution was consistent, with only a minor decrease in the conflict rate of region 3 – Eastern Europe. This is not surprising as many of the countries included in this region were a part of the USSR during the timeframe 1970-1991.

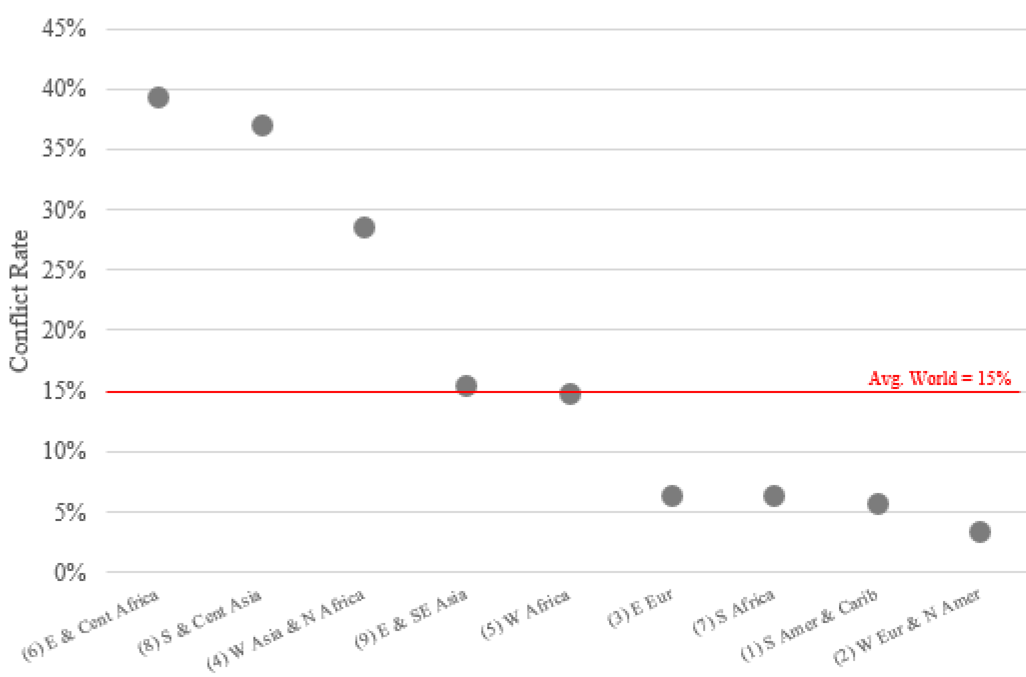

Figure 1 – Conflict Rate by Region: Conflict rate is the number of country-years with at least one conflict-event divided by the total number of country-years in the dataset. Already we can see that there are heterogeneous rates of conflict among the nine regions.

Primary Variable of Interest

This paper will primarily investigate the relationship between conflict occurrence and the size of the youth cohort within a country and year. Youth Cohort is defined as the percentage of the adult population between the ages of 15-24 and is published by the U.N. World Population Prospects (United Nations, 2022). A visual examination of the bivariate relationship between youth cohort size and conflict occurrence indicates that there does appear to be some positive relationship between the two (Figure 2). Conflict occurrence seems particularly likely when the youth cohort size is between 18-24% of the adult population. At first glance this seems to decrease beyond 24%, however there are very few country-years where the youth cohort size exceeds this percentage (only 31 out of a sample of 5,022).

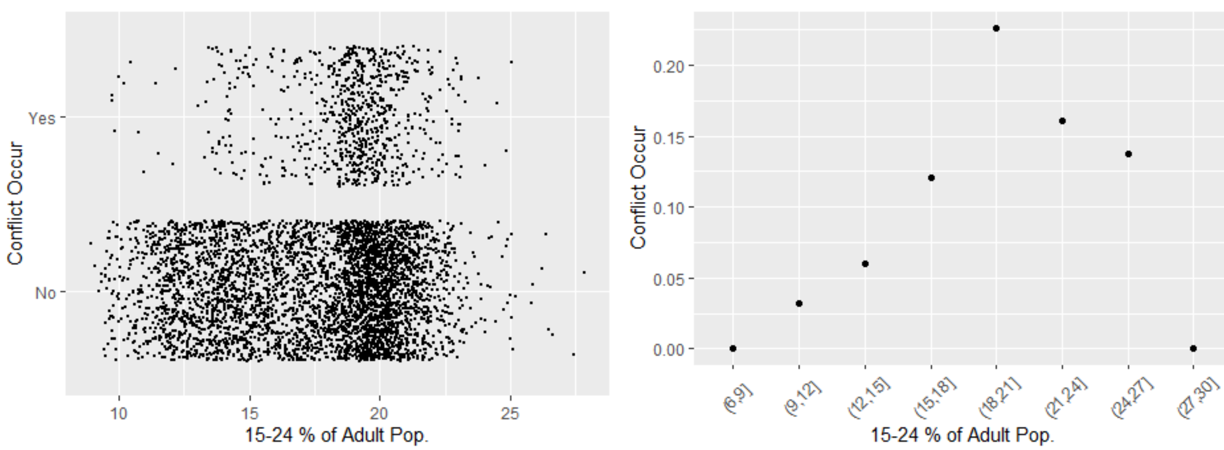

Figure 2 – Conflict Outcome versus Youth Cohort Size

Additional Model Variables

Total population, Youth Bulge (proportion of the total adult population aged 15-24), and Infant Mortality Rate (IMR) were derived from the UN World Population Prospects. Per-capita GDP was drawn from the Penn World Table, which is expressed in international-$ at 2017 prices and adjusted for inflation as well as for cost of living between countries (Feenstra, 2015).

Educational attainment was sourced from the UNESCO Educational Attainment dataset and is defined as the percentage of the adult population that has attained at least a lower secondary-school level. This threshold was used as there are different educational structures in different countries, and the standard 12-grade system that the United States uses is not applicable or available in some settings. Lower secondary-school level (typically reach by age 15-16) is more prevalent and offers a better way to compare nation-level educational attainment across countries. Political regime type utilizes the Polity V data to measure regime type and the variable ranges from -10 (most autocratic) to 10 (most democratic). In order to capture regional effects, I am using a multilevel model (MLM) with regions based on classifications from Hegre et al. 2013. Figure 3 displays a map of the regions by country.

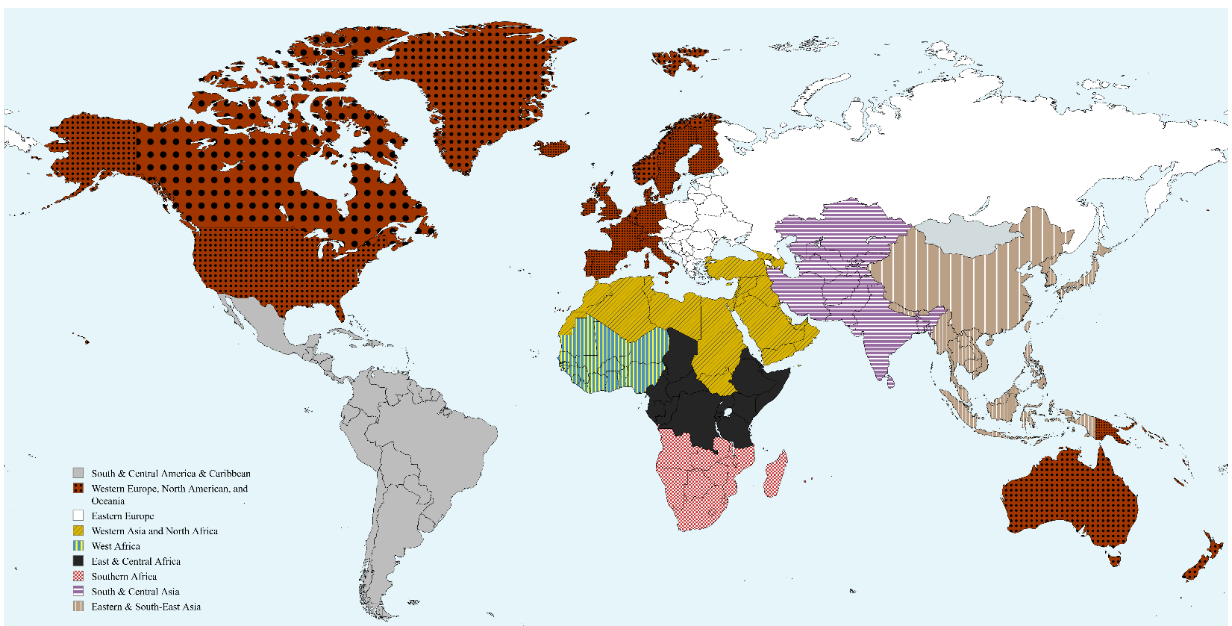

Figure 3 - Map of Regions: South & Central America & Caribbean (30), Western Europe, North America, and Oceania (25), Eastern Europe (24), Western Asia and North Africa (25), West Africa (16), East & Central Africa (16), Southern Africa (14), South & Central Asia (12), Eastern & South-East Asia (24).

Data Transformations

For this analysis, Total Population as well as Per-capita GDP have been log transformed. This is to linearize the relationship, stabilize the variance, and compress the difference between large values (making the regression less sensitive to outliers). This is especially pertinent for population and financial variables (which typically get into the hundreds of thousands or millions). Additionally, Youth Cohort, Infant Mortality Rate (IMR) and Educational Attainment have been z-score transformed. These variables are on limited scales compared to population and per-capita GDP figures, and this transformation improves both numerical stability (to account for the smaller range of values) and makes the coefficients comparable. The Polity Score variable, which ranges from -10 to 10, has also been transformed by taking the absolute value. As noted in the previous section, and as can be seen in Figure B5 of Appendix B, the relationship between Polity Score and conflict occurrence exhibits a pyramid shape, with countries that have neither a strong autocratic (score close to -10) nor a strong democratic (score close to 10) political regime being most prone to conflict. The absolute value transformation preserves this linear directional relationship.

Full data for all countries and years used in the analysis was available for all variables except Educational Attainment, which had 28% of its country-year values missing. Because logistic regression excludes missing data this could bias the analysis and so imputation on the Educational Attainment variable was used. Instead of using a simple global mean-value imputation, a two-step process was used. In the first step, the mean Educational Attainment value was calculated for each country and decade (1992-1999, 2000-2009, 2010-2018). This country-decade mean value was imputed for countries that were missing some values but had other values available within the same decade. Educational Attainment values are assumed to have a stickiness feature (in that their variance is limited within any particular decade) as it is difficult to substantially change the lower-secondary-school completion rate on a national level from one year to the next. After this first step, 15% of Educational Attainment country-year values were missing. The second step used the mean Educational Attainment value for each region-decade. Countries within each region are assumed to have similarities in their Educational Attainment characteristics. After the second step of imputation, Education Attainment contained zero missing values and all cases could be included in the logistic regression analysis.

Methodological Approach

This analysis utilizes a Bayesian inference framework, which incorporates prior information into inferences, provides probabilistic information on those inferences, and can be represented by random simulations (Gelman, 2021). Model fitting and posterior approximation is done via Markov Chain Monte Carlo (MCMC) simulation with the rstanarm package. rstanarm emulates other R model-fitting functions (such as those that utilize Maximum Likelihood Estimation) but allows one to fit regression models using the statistical inference engine Stan for back-end estimation (Goodrich, 2019). The motivation for using the Bayesian framework with MCMC simulation is to be able to summarize the uncertainty in the estimation of the models and go beyond simple confidence intervals and statistical significance (via p-values).

Additionally, as will be explained in detail in the Model 2 section below, this analysis will utilize a Bayesian multilevel model that accounts for regional differences while partially pooling estimates from regions with less informative data toward the global estimate. This captures systematic and random variation in heterogeneous effects, estimates effects within each region, and measures effect variance (Alley, 2023). This provides a balance between running nine individual regression and only one global regression.

Model 1: Complete Pooling (Global Model)

I will be using bivariate logistic regression to model the occurrence of conflict based on the various predictors outlined previously. After analyzing a global structure that excludes region-level effects, I will expand the base model into a multilevel structure. Furthermore, this analysis will utilize a Bayesian framework, which emphasizes incorporating prior information, quantifying the uncertainty in the estimated parameters, and checking the models via posterior model checks. As explained in the prior section, the outcome for this model is the occurrence of 1 or more conflict events in a given country-year. Let Y_i be the 0 / 1 indicator of conflict-event-occurrence for any given country year *i*. Then, the Bayesian logistic regression model (without region-level effects) of Y is:

$$Y_i|\beta_0, \cdots, \beta_7 \sim \text{Bern}(\pi_i) \;\; \text{with} \;\; \log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_7 X_{i7}$$

$$\beta_0 \sim N(-1.7, 1.5^2)$$

$$\beta_1 \sim N(0, 2.5^2)$$

$$\vdots$$

$$\beta_7 \sim N(0, 2.5^2)$$

To start, consider the prior tunings. As the parameters can take on any value on the real line, Normal priors are appropriate. Beginning with the intercept, β_0 , using the UCDP conflict dataset from 1970 – 2018, there is an average conflict rate of ~15% for any given country-year. This is a reasonable prior center for the analysis. Then, the prior mean for β_0 can be set, on the *log(odds)* scale, to:

$$\log\left(\frac{\pi}{1-\ \pi}\right)\ =\ \log\left(\frac{0.15}{1-\ 0.15}\right)\ \approx\ -1.7$$

To account for uncertainty in the probability of conflict, I will be using weakly informative priors. That is, the range of the intercept prior (as well as subsequent priors on other parameters) will be relatively wide to incorporate some prior knowledge and stabilize the posterior estimation (as opposed to using uninformative priors) while avoiding giving too much weight to the prior specifications and allowing the data to speak for itself. A reasonable range on the intercept is (-1.7 $\pm$ 2*1.5), which, on the *log(odds)* scale, indicates that a 95% interval (two standard deviations away from the mean) for the probability of conflict would be in the range of 0.01 to 0.79.

Prior understanding of how predictors are related to conflict occurrence is less certain when controlling for other predictors, i.e. a multivariate model. Because of this, I will utilize weakly informative priors for these coefficients. However, because there is prior research available in this field (much of which was described in the Literature Review), Table A1 in Appendix A gives an overview of select previous estimates and standard errors for the included model variables. These can be compared to the estimated coefficients of the model to gauge consistency versus prior research.

Model 2: Partial Pooling (Multilevel Model)

In the second part of the analysis, in order to account for differences in regions, I will expand the above to a multilevel logistic model. Again, this will model the occurrence of a conflict in a county-year given the factors specified in the previous section. The multilevel model specification is as follows:

$$Y_{ij}|\beta_{0j}, \cdots, \beta_{7j} \sim \text{Bern}(\pi_{ij}) \text{ with}$$

$$\log\left(\frac{\pi_{ij}}{1 - \pi_{ij}}\right) = \beta_{0j} + \beta_{1j}X_{ij1} + \cdots + \beta_7 X_{ij7}$$

$$\beta_{0j}|\, \beta_0, \sigma_0 \sim N(\beta_0, \sigma_0^2)$$

$$\beta_0 \sim N(-1.7, 1.5^2)$$

$$\beta_1 \sim N(0, 2.5^2)$$

$$\vdots$$

$$\beta_7 \sim N(0, 2.5^2)$$

$$\sigma_0 \sim \text{Exp}(1)$$

Consider the assumptions behind, and the meaning of, the model parameters. The region-specific intercepts, β_{0j}, describe the underlying conflict rates, as measured by the log (odds of conflict) for each region j. These imply that some regions are inherently more prone to conflict than others (Johnson, 2021). At first glance, this may seem like a strong assumption. However, recall from Figure 1 the shape of the distribution of conflict rates among the various regions. The multilevel model recognizes the existence of data clustering by allowing for residual components at each region in the model, while being Normally distributed around a global intercept, β_0 . The residual variance is then partitioned into a between-region component and a within-region component (Alley, 2023). The subsequent parameters $\beta_1 \cdots \beta_7$ describe the global relationship between conflict and their respective variables when adjusting for the other variables.

Results

Model 1: Global Model

Before investigating the multilevel model on world region, it is worth looking at the estimates from the global model for comparison:

Global Logistic Model (no multilevel structure)

	mean	se	10%	50%	90%	Divide-by-four (mean)
(Intercept)	-6.94	0.94	-8.14	-6.94	-5.75	
Total Population (log)	0.55	0.05	0.49	0.55	0.61	13.7%
Youth Cohort (z-score)	0.15	0.11	0.01	0.15	0.28	3.7%
Conflict Prior Year	4.38	0.14	4.21	4.38	4.56	110%
Educational Attainment (z-score)	0.01	0.11	-0.14	0.01	0.15	0.2%
IMR (z-score)	0.18	0.11	0.04	0.18	0.32	4.4%
Polity Regime (abs val)	-0.14	0.03	-0.18	-0.14	-0.11	-3.6%
Per-Capita GDP (log)	-0.10	0.09	-0.22	-0.09	0.02	-2.4%

Table 1: Global-level model with no multilevel structure on regions.

Appendix C contains diagnostic plots to check the stability of the MCMC simulation results. The trace plots (Figure C1) indicate stable traversal of the sample space via the chains.

The density plots (Figure C2) also confirm that the chains produce nearly indistinguishable posterior approximations, providing evidence that the simulation is stable and sufficiently long. Lastly, the lag plots in Figure C3 indicate that autocorrelation among the chains drops off quickly, confirming that the chain is mixing quickly and moving around the range of plausible posterior parameter values, mimicking an independent sample (Johnson, 2021).

Looking into the estimated coefficients, while there are varying estimates depending on the predictor, the means are in the anticipated directions. Educational Attainment is the only exception; the model implies that as one moves a standard deviation from the mean (due to the z-score transformation), there is an associated slight increase in the probability of conflict. There is much uncertainty in this estimate, however, as the 80% credible interval ranges from -0.14 to 0.15. Coefficients in a logistic regression model can most easily be interpreted using the divide-by-four rule. As the logistic curve is steepest at its center (where $logit^{-1}(\alpha + \beta x) = 0.5$), the slope of that curve is maximized at that point and attains the value β / 4. This value is then the maximum difference in the probability of the outcome occurring for a unit difference in the predictor. Thus, dividing each estimated coefficient by 4 gives an upper bound of the predictive difference corresponding to a unit difference in the predictor (Gelman, 2021). For instance, in the case of Youth Cohort (z-score), for an increase in one standard deviation from the mean in the proportion of an adult population in the age range 15-24, we anticipate an increase in the probability of conflict of (0.15 / 4) = 3.7%. This is, indeed, an interesting finding, and in fact the estimate is on roughly the same level as IMR, Polity Regime, and Per-Capita GDP (although with these last two the predictor is associated with the outcome in the opposite direction). Not surprisingly, as previous research has indicated, there is a stickiness to conflict, and conflict in the prior year is substantially associated with continued conflict (4.38 / 4 = 110%). Comparing two country-years, with other variables held equal, a country that saw conflict in the preceding year has more than double the chance of conflict in the following year compared to a country that did not see conflict in the preceding year. Finally, Polity Regime has a slightly different interpretation in light of the absolute value transformation. The original scale was from -10 to 10 (fully autocratic to fully democratic), which was transformed to 0 through 10. Therefore, an increase of 1 on the transformed Polity scale indicates a country's political regime becoming more structured, regardless of the direction of that structure (more authoritarian or more democratic). The negative coefficient (-0.14 / 4 = -3.6%) indicates that countries with stronger political regimes (in either direction) are associated with less probability of conflict compared to countries with weaker political regimes. This reflects the pyramid pattern observed in Figure B5.

To evaluate the quality of this initial global model, Figure 4 presents a posterior predictive check to confirm that the simulated data from the posterior model has features similar to the original data, and the assumptions underlying it are reasonable (Johnson, 2021). This consistency is met, with most of the posterior simulated datasets close to the observed conflict incidence.

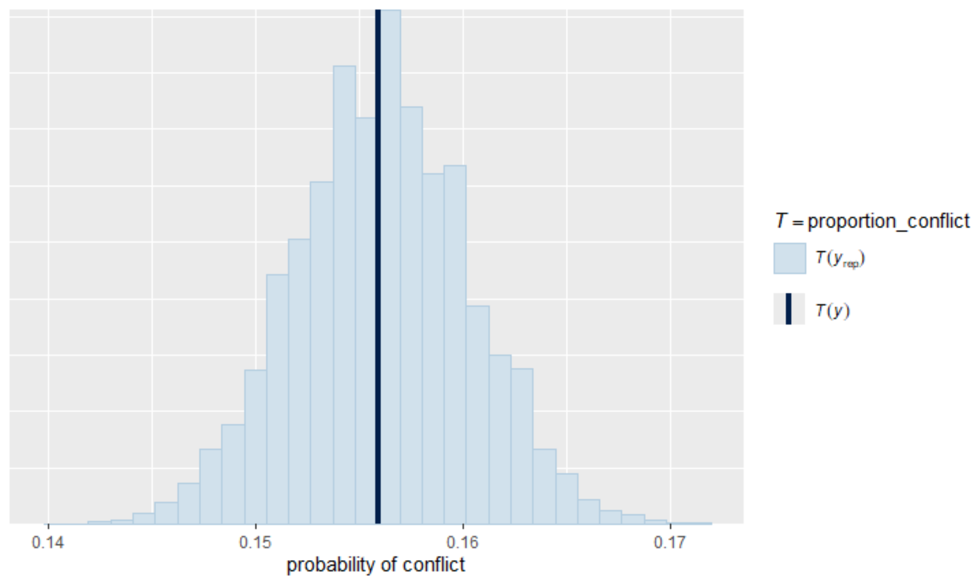

Figure 4 – Posterior Predictive Check of Global Model: Histogram displays the proportion of conflict occurrence in each of 100 posterior simulated datasets. Vertical line represents the observed proportion of years with a conflict event.

To evaluate predictive and generalization performance, leave-one-out (LOO) log prediction probabilities are used to compute the LOO log score for the global model. Higher values of log scores indicate better models (Gelman, 2021). For a simple comparison, the log score of a simple intercept model on this data is -3481. The global model produces a LOO log score of -839, indicating a much better model. This is not surprising at all, given that the global model includes a lot more information, but this LOO log score will be used below to compare the global model to the multilevel model.

Model 2: Multilevel Model (Varying Intercepts on Region)

Although the global model does align with previous research, we start to see some differences when we move to a multilevel structure by region. The model estimates in this case are in Table 2:

Multilevel Model (on Region): Varying Intercepts

	mean	sd	10%	50%	90%	Divide-by-four (mean)
(Intercept)	-7.75	1.02	-9.08	-7.75	-6.44	
Total Population (log)	0.58	0.05	0.51	0.58	0.64	14.4%
Youth Cohort (z-score)	-0.01	0.12	-0.17	-0.01	0.15	-0.2%
Conflict Prior Year	4.22	0.14	4.04	4.22	4.40	106%
Educational Attainment (z-score)	-0.17	0.13	-0.34	-0.17	-0.01	-4.4%
IMR (z-score)	0.21	0.12	0.06	0.21	0.36	5.2%
Polity Regime (abs val)	-0.12	0.03	-0.15	-0.12	-0.09	-3.0%
Per-Capita GDP (log)	-0.05	0.10	-0.18	-0.05	0.08	-1.4%
(Intercept) Region 1	-0.33	0.28	-0.68	-0.32	0.02	-8.2%
(Intercept) Region 2	-0.39	0.34	-0.82	-0.38	0.03	-9.8%
(Intercept) Region 3	0.10	0.32	-0.30	0.09	0.50	2.4%
(Intercept) Region 4	0.84	0.25	0.53	0.84	1.16	21.0%
(Intercept) Region 5	-0.31	0.29	-0.68	-0.30	0.05	-7.8%
(Intercept) Region 6	0.36	0.27	0.02	0.35	0.70	8.9%
(Intercept) Region 7	-0.60	0.34	-1.04	-0.58	-0.17	-14.9%
(Intercept) Region 8	0.31	0.28	-0.05	0.30	0.67	7.6%
(Intercept) Region 9	-0.20	0.26	-0.53	-0.20	0.13	-5.1%

Table 2: Multilevel Varying-Intercepts model on regions.

Prior to interpreting the model coefficients, Appendix D contains diagnostic plots to check the stability of the MCMC simulation results. The trace plots (Figure D1) indicate stable traversal of the sample space via the chains. The density plots (Figure D2) also confirm that the chains produce nearly indistinguishable posterior approximations, providing evidence that the simulation is stable and sufficiently long. The lag plots in Figure D3 also indicate that autocorrelation among the chains drops off quickly, confirming that the chain is mixing well.

A posterior predictive check (Figure 5) confirms that the simulated data from the posterior model has features similar to the original data, and the assumptions underlying it are reasonable. The multilevel model produces a LOO log score of -820. Compared to the score for model 1 (-839), the multilevel structure appears to produce a better model.

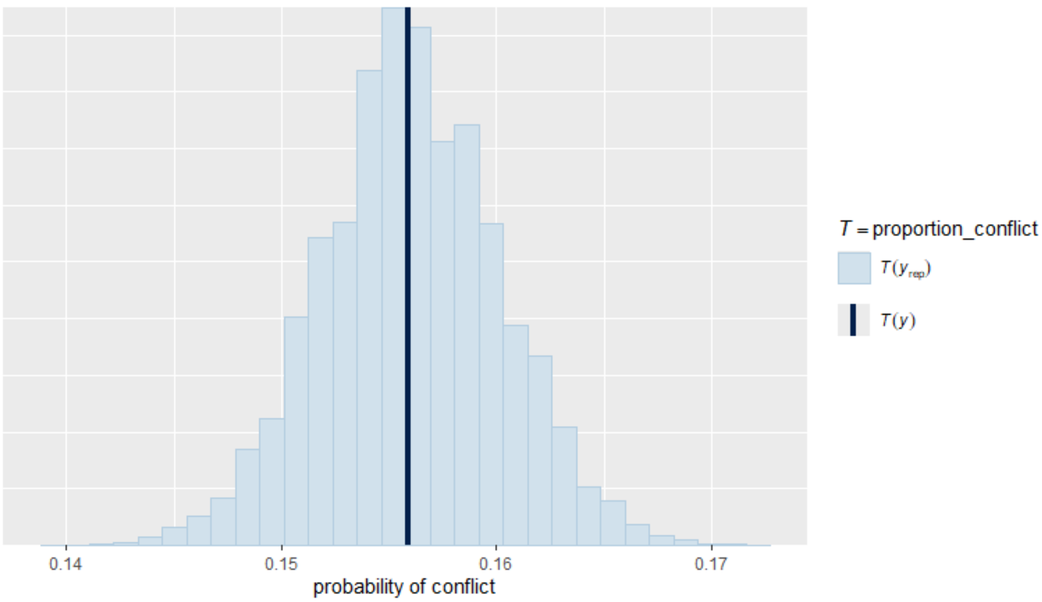

Figure 5 – Posterior Predictive Check of Multilevel Model: Histogram displays the proportion of conflict occurrence in each of 100 posterior simulated datasets. Vertical line represents the observed proportion of years with a conflict event.

Once we introduce a multilevel structure to the model, we see an interesting shift in the estimates for both Youth Cohort and Educational Attainment. Estimates for the other predictors only move slightly with the additional multilevel structure, yet those of Youth Cohort and Educational Attainment drop substantially and switch signs. For Educational Attainment this is not so surprising, as there already existed large variation in the global estimate. The change in the Youth Cohort coefficient, however, implies that much of the association of Youth Cohort on the outcome of civil conflict occurrence is absorbed by the regional intercept variation regions. Indeed, we see significant differences in the mean estimated intercepts for the different regions, going from -0.6 for Region 7 (Southern Africa) to +0.84 for Region 4 (Western Asia and North Africa). While the differences in intercepts as a whole is not too surprising, since conflict does tend to cluster in particular areas, the drop in the estimate for Youth Cohort is concerning and implies that effects researchers have seen in previous global-level studies may be driven by regional factors.

Model 3: Multilevel Model (Varying Intercepts and Youth Cohort Slopes on Region)

Extending the model a bit further, we can investigate a multilevel structure with both the intercepts and Youth Cohort coefficients varying by region. The model estimates for this structure are displayed in Table 3. Although not reproduced in this paper, the posterior predictive checks confirmed that the posterior model was stable and consistent with models 1 and 2. The varying-intercepts and slopes model produces a LOO log score of -819 which, compared to the score for model 2 (-820) is slightly better but on-par with the varying-intercepts-only model.

We see large substantial variation in the Youth Cohort estimates when that predictor is included in the multilevel model structure. All of the estimates are within 2-standard errors from zero, indicating large variation. Additionally, the mean Youth Cohort slope estimates among the regions mostly point in the opposite direction than previous research would expect. For instance, although Region 4 (W Asia and N Africa) begins with a higher probability of conflict compared to the baseline (as indicated by the large positive estimate for its regional intercept, 0.88), the varying Youth Cohort mean estimated coefficient for this region is -0.24, indicating that as the percentage of the 15-24 cohort increases in this region the probability of conflict is predicted to decrease. This is not strong evidence, however, as all of the 80% credible intervals for these coefficients cross zero. All of this taken together implies that, although on a global-level we may see youth bulges associated with higher risk of conflict, this relationship appears to break down when we introduce a multilevel structure on regions.

Multilevel Model (on Region): Intercept and Youth Cohort Slope

	mean	sd	10%	50%	90%	Divide-by-four (mean)
(Intercept)	-8.05	1.05	-9.39	-8.06	-6.70	
Total Population (log)	0.60	0.05	0.53	0.60	0.66	14.9%
Youth Cohort (z-score)	-0.01	0.18	-0.24	0.00	0.22	-0.2%
Conflict Prior Year	4.20	0.14	4.02	4.20	4.38	105%
Educational Attainment (z-score)	-0.18	0.13	-0.35	-0.18	-0.01	-4.5%
IMR (z-score)	0.20	0.12	0.05	0.20	0.35	5.1%
Polity Regime (abs val)	-0.12	0.03	-0.16	-0.12	-0.09	-3.0%
Per-Capita GDP (log)	-0.04	0.10	-0.17	-0.04	0.09	-0.9%
(Intercept) Region 1	-0.41	0.30	-0.80	-0.40	-0.04	-10.3%
(Intercept) Region 2	-0.28	0.35	-0.72	-0.27	0.16	-6.9%
(Intercept) Region 3	0.00	0.34	-0.43	0.01	0.42	0.1%
(Intercept) Region 4	0.88	0.27	0.55	0.87	1.23	22.0%
(Intercept) Region 5	-0.26	0.33	-0.68	-0.26	0.15	-6.5%
(Intercept) Region 6	0.33	0.32	-0.07	0.32	0.73	8.1%
(Intercept) Region 7	-0.50	0.38	-0.99	-0.49	-0.04	-12.6%
(Intercept) Region 8	0.30	0.30	-0.08	0.29	0.68	7.4%
(Intercept) Region 9	-0.28	0.27	-0.62	-0.27	0.06	-6.9%
(Youth Cohort) Region 1	0.12	0.27	-0.18	0.10	0.46	3.1%
(Youth Cohort) Region 2	0.28	0.27	-0.02	0.23	0.64	6.9%
(Youth Cohort) Region 3	-0.08	0.23	-0.36	-0.07	0.17	-2.1%
(Youth Cohort) Region 4	-0.24	0.24	-0.54	-0.23	0.04	-6.0%
(Youth Cohort) Region 5	-0.09	0.33	-0.50	-0.04	0.27	-2.2%
(Youth Cohort) Region 6	0.02	0.28	-0.30	0.00	0.37	0.5%
(Youth Cohort) Region 7	-0.13	0.36	-0.59	-0.07	0.26	-3.2%
(Youth Cohort) Region 8	-0.06	0.24	-0.35	-0.05	0.23	-1.4%
(Youth Cohort) Region 9	0.21	0.23	-0.05	0.18	0.52	5.3%

Table 3: Multilevel Varying-Intercepts-Slope (Youth Cohort) model on regions.

Posterior Prediction

One of the benefits of using a Bayesian framework is that we can utilize the posterior predictive distribution from the MCMC simulation to make predictions (with probabilities) on unseen data. To further assess the ability of Model 2 (varying intercept multilevel model) to predict conflict, I will use data similar to the original dataset but encompassing the years 2019-2021. This data was withheld from the original analysis due to missing data on some variables (specifically Polity Regime, Per-capita GDP, and Educational Attainment). I used the same imputation process as described in the Data and Methods section to complete the dataset. There were 558 new observations in this data, with 103 having one or more conflict occurrences.

The posterior prediction process (via rstanarm) generates 20,000 outcome (conflict or no conflict) predictions for each of the 558 new observations. By summarizing the proportion of positive (outcome = 1) predictions we can get a predicted probability of conflict for each of the new country-years. Using a threshold of > 50% probability, considered a relatively high bar for classifying conflict predictions (Hegre et al. 2021), Figure 6 displays the confusion matrix for conflict outcome:

> 50% prob		**Actual**			
		Conflict	No Conflict		
Predicted	Conflict	92	0	Accuracy:	0.98
	No Conflict	11	455	Precision:	1.00
		103	455	Recall:	0.89

Figure 6 – Confusion Matrix for Model 2 Posterior Prediction: Displays the predicted outcome based on 50% probability of the 2019-2021 conflict dataset. Performance metrics are displayed on the right.

Overall, Model 2 predicts very well, even at the 50% probability threshold, on new data. There are zero false positives and the model's accuracy (overall correctness) is 98%. There were 11 instances where the model predicted "no conflict" when conflict actually occurred (false negatives). These instances occurred in countries such as Ethiopia, Israel, Azerbaijan, Rwanda, and Tanzania. Most of these occurrences were conflicts that seemed to stem from tensions between competing groups (ethnic, cultural or otherwise). This demonstrates that while models, even at the regional level, that utilize economic and developmental variables appear to do a very good job of modeling and predicting conflict events, there are still factors beyond these that need to be studied and understood to get a full picture of when conflict may erupt.

Discussion

In light of the results from the above models, this paper highlights that there are limitations in existing civil conflict models that emphasize global-level economic and developmental variables. Once a multilevel structure is introduced, the findings suggest that regional factors play a significant role in shaping the occurrence of civil conflicts, particularly in regard to the youth cohort variable. The exact nature of the regional factors, however, needs to be studied further. Concepts such as shared history, regional power dynamics, ethnic ties and religious affiliations could certainly influence the motivations of various participants in conflict. Although existing models perform well at predicting where conflict could occur, especially when a regional-structure is implemented, there are enough cases where conflict was not predicted but occurred that suggest there is another piece missing, especially in locations where conflict has not occurred in the recent past.

Considering the spatial dimensions of civil conflict may go some way in improving models. Regional factors, such as the spillover effects of neighboring conflicts or the influence of regional powers, could have a substantial impact on conflict onset. Similarly, cultural factors, often intimately tied to geographic regions, can influence conflict as well. These are issues such as long-standing grievances or historical tensions between groups. By recognizing the significance of regional and cultural factors, interventions can be tailored to address particular challenges of each conflict context. This may involve group dialogue and understanding, processes that address historical grievances, or structures that nurture regional cooperation.

It may also be that there is a need for more interdisciplinary ties when studying civil conflict. There may be insights from fields such as sociology and anthropology that can supplement current understanding of the complex dynamics and factors at work. An interdisciplinary perspective could lead to development of regional-focused and nuanced understanding conflict anticipation and prevention.

Conclusion

This paper proposed to model the factors that influence and predict civil conflict within countries. The data consisted of conflict events that occurred in all significant countries for the period 1992-2018 as well as country-level variables that account for economic and developmental factors. After building a global-level model that is consistent with the current conflict literature, I went further and introduced a regional-level structure through Bayesian multilevel modeling. This framework allowed the model to both incorporate prior information from previous literature and account for regional-level factors that may not have been included in studies that only focus on the global estimates. The multilevel structure provides additional insight into the various factors affecting the propensity of countries towards civil conflict. Although the strongest factors such as Total Population and per-capita GDP appear to remain strong even when regional structure is introduced, other factors that may have had a more tenuous association appear to break down. This would suggest that models for civil conflict need to be more carefully constructed in the future. Simple, global-level analyses should be augmented with more robust, multilevel structures, as the regional affects appear to be very strong. In particular, the impact of Youth Cohorts on propensity of civil conflict needs to continue to be reviewed. This analysis sheds some doubt on how strong this relationship really is. It may be that the associations that "youth bulges" have seen in past research may simply be a relic of regional and other socioeconomic factors. Additional work should be done to measure the impact at a lower level, perhaps at the provincial or city level. Regional and cultural factors can be studied, possibly through interdisciplinary approaches. Although we do currently have a great foundation that goes a long way toward understanding conflict, there continues to be more work that needs to be done to study how conflict arises and how we may best use resources to prevent it.

Appendix A

	Fearon, 2003				Urdal, 2006				Wimmer, 2009				Hegre, 2013				Yair, 2014			
	Model A		Model B		Model A		Model B		Model A		Model B		Model A		Model B		Model A		Model B	
Predictor	mean	se	mean	se	mean	se	mean	se	mean	se	mean	se	mean	se	mean	se	mean	se	mean	se
GDP per capita							-0.262	0.114	-0.092	0.039	-0.097	0.044					-0.401	0.139		
Per capita income	-0.344	0.072	-0.379	0.100																
Infant Mortality Rate					0.006	0.002							0.027	0.332	0.049	0.339			0.007	0.002
Population Size	0.263	0.073	0.389	0.110	0.271	0.003	0.229	0.050	0.383	0.077	0.382	0.083	0.353	0.099	0.373	0.104	0.292	0.073	0.365	0.078
Regime Type					0.011	0.014	0.008	0.014												
Education													-1.633	0.835	-1.438	0.855				
15-24 Cohort (youth bulge)					0.043	0.017	0.044	0.019					0.013	0.039	-0.016	0.041	0.016	0.025	0.032	0.022
Prior Conflict	-0.954	0.314	-0.849	0.388									2.671	1.814	1.628	1.958				
Anocracy ^	0.521	0.237									0.457	0.237					1.268	0.223	1.255	0.220
Brevity of Peace					1.887	0.268	1.808	0.260												
Peace Years									-0.088	0.6913	-0.131	0.6827					-0.005	0.009	-0.001	0.011

^ an indicator varible for if a country's political regime is neither democratic nor authoritarian

Table A1: Mean estimates and standard errors on coefficients of interest from a representative sample of previous research in conflict research

Appendix B

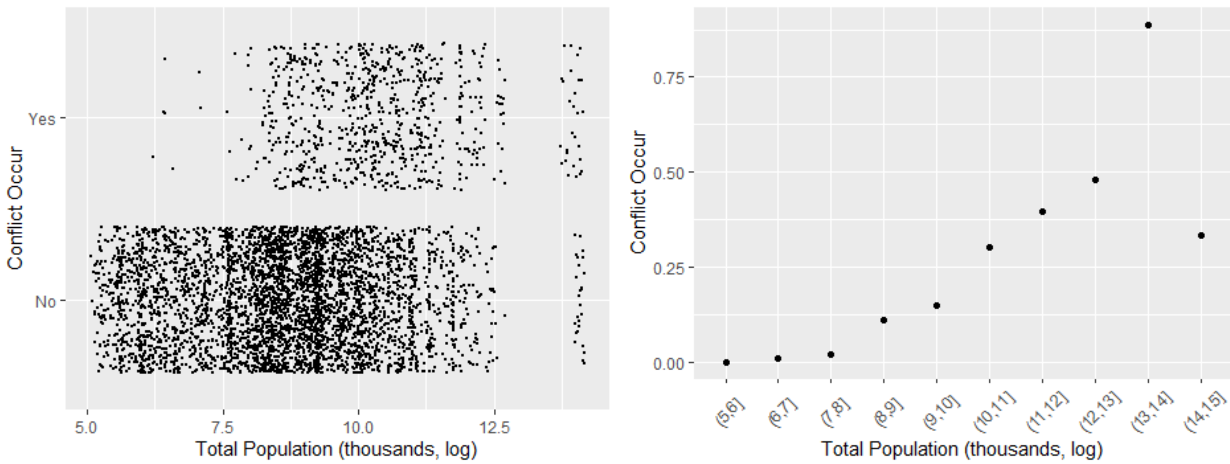

Figure B1 – Conflict Outcome versus Total Pop. (in thousands, log)

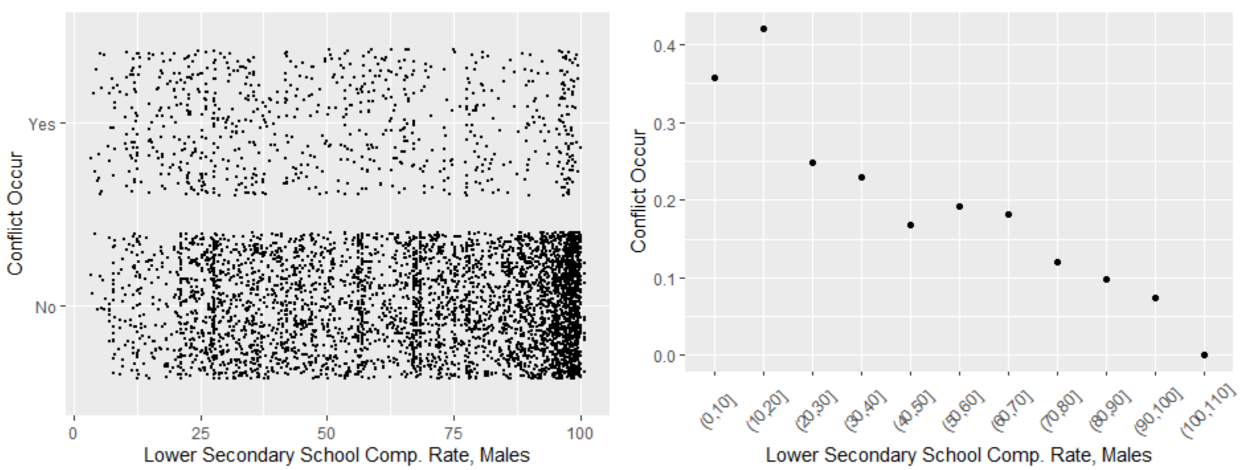

Figure B2 – Conflict Outcome versus Educational Attainment

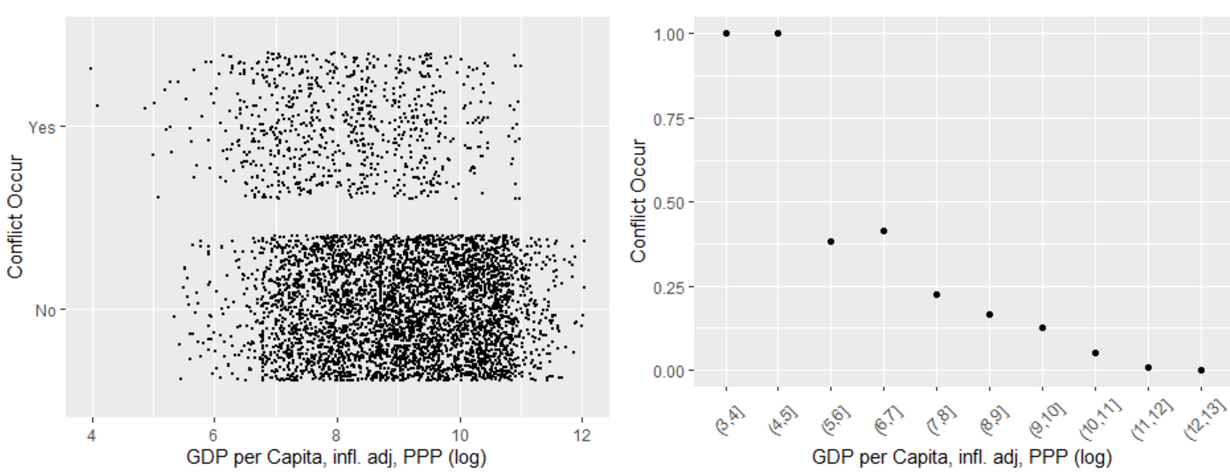

Figure B3 – Conflict Outcome versus GDP per Capita, infl. adj, PPP (log)

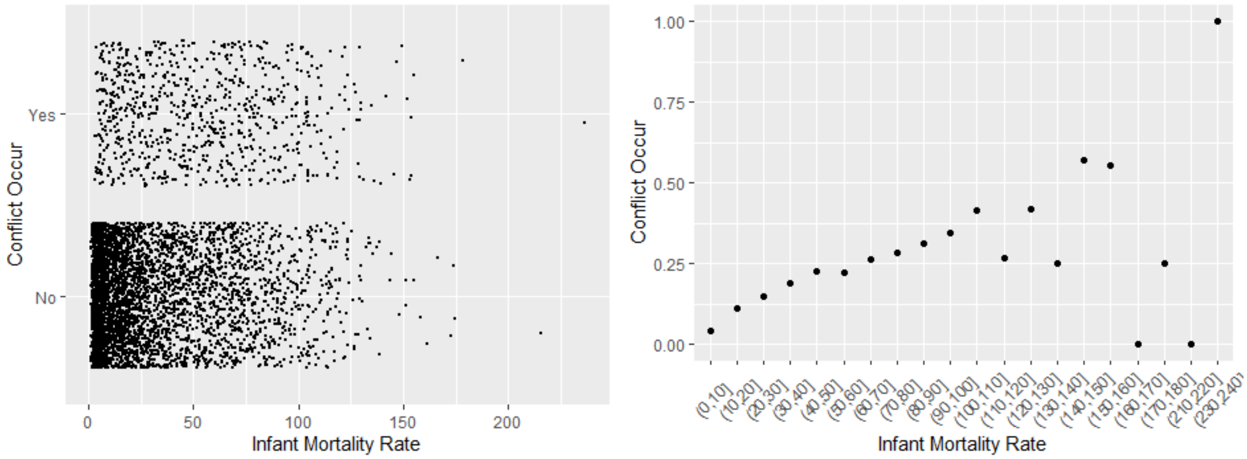

Figure B4 – Conflict Outcome versus Infant Mortality Rate

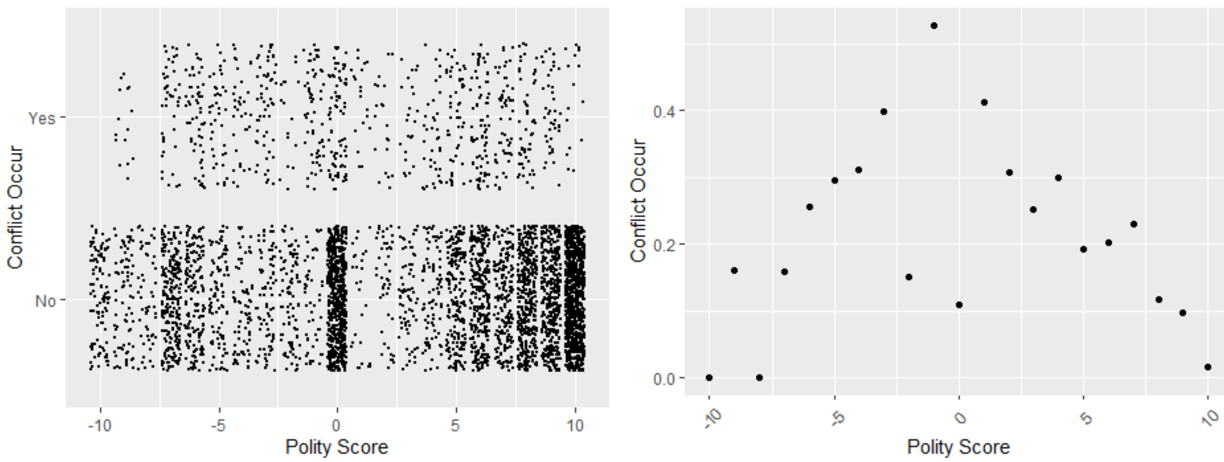

Figure B5 – Conflict Outcome versus Polity Score (-10 to 10 scale)

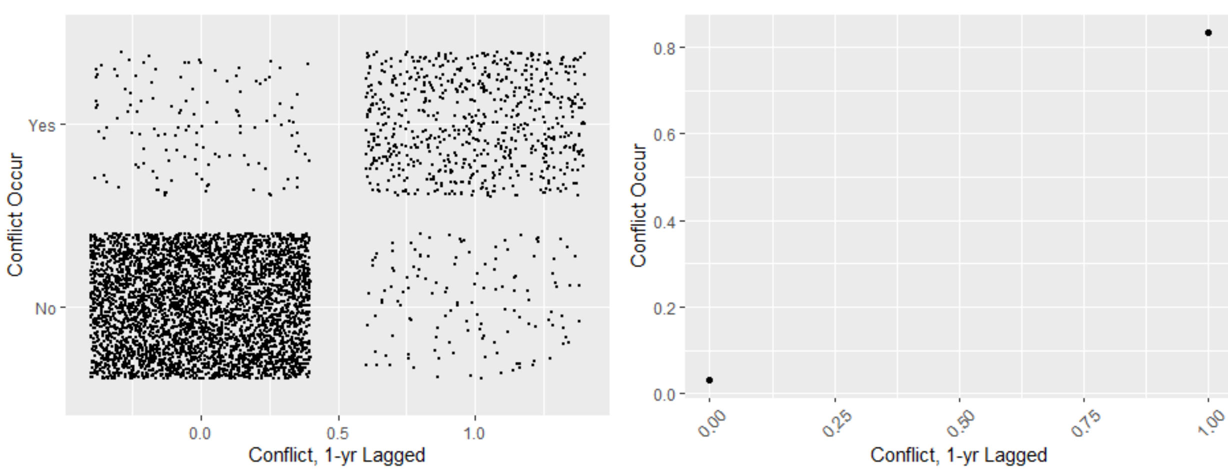

Figure B6 – Conflict Outcome versus Conflict 1-yr Lagged Indicator

Appendix C

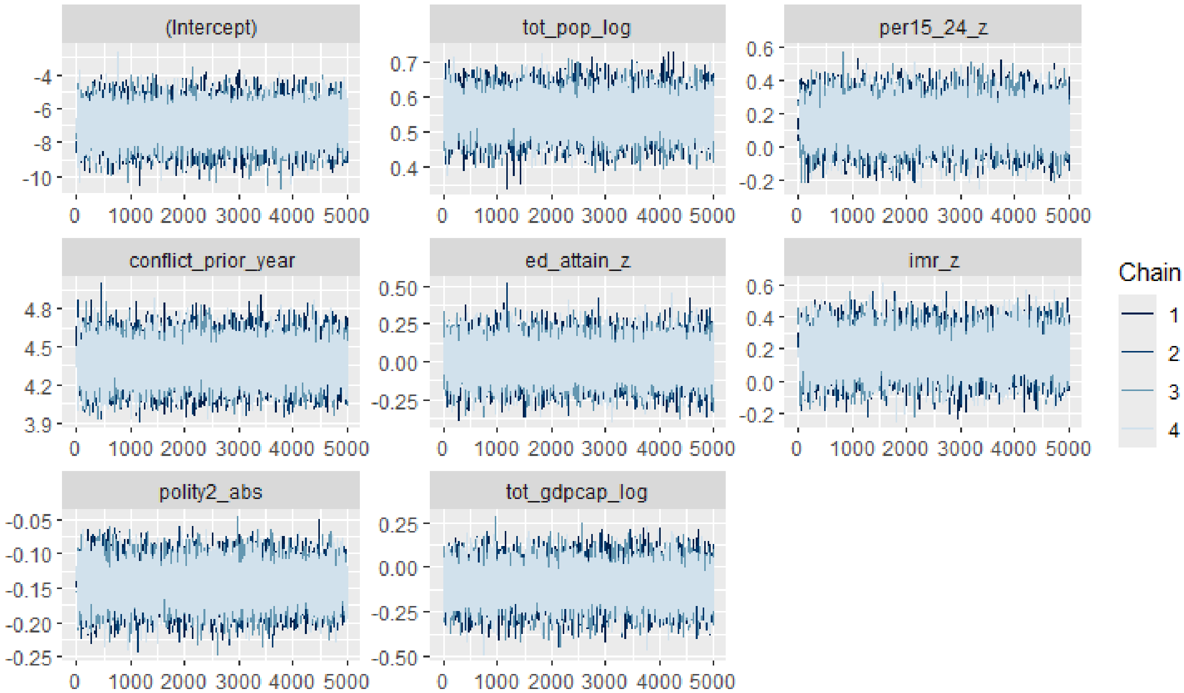

Figure C1 – MCMC trace plots for global conflict occurrence model parameters

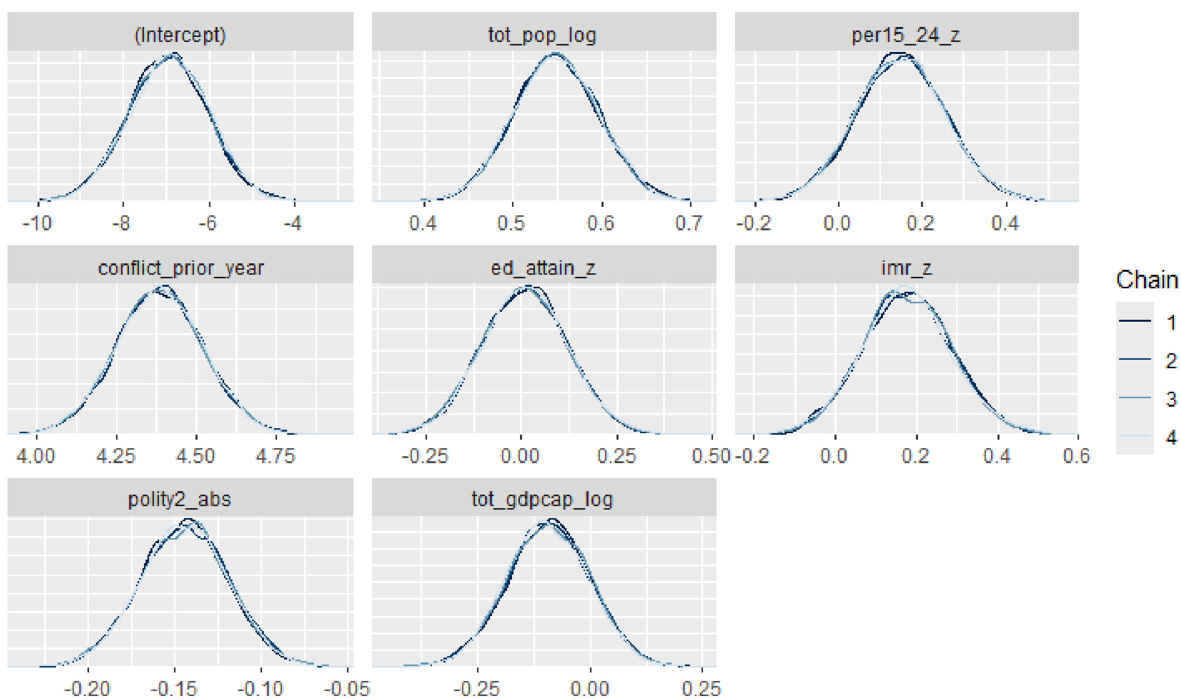

Figure C2 – MCMC density plots for global conflict occurrence model parameters

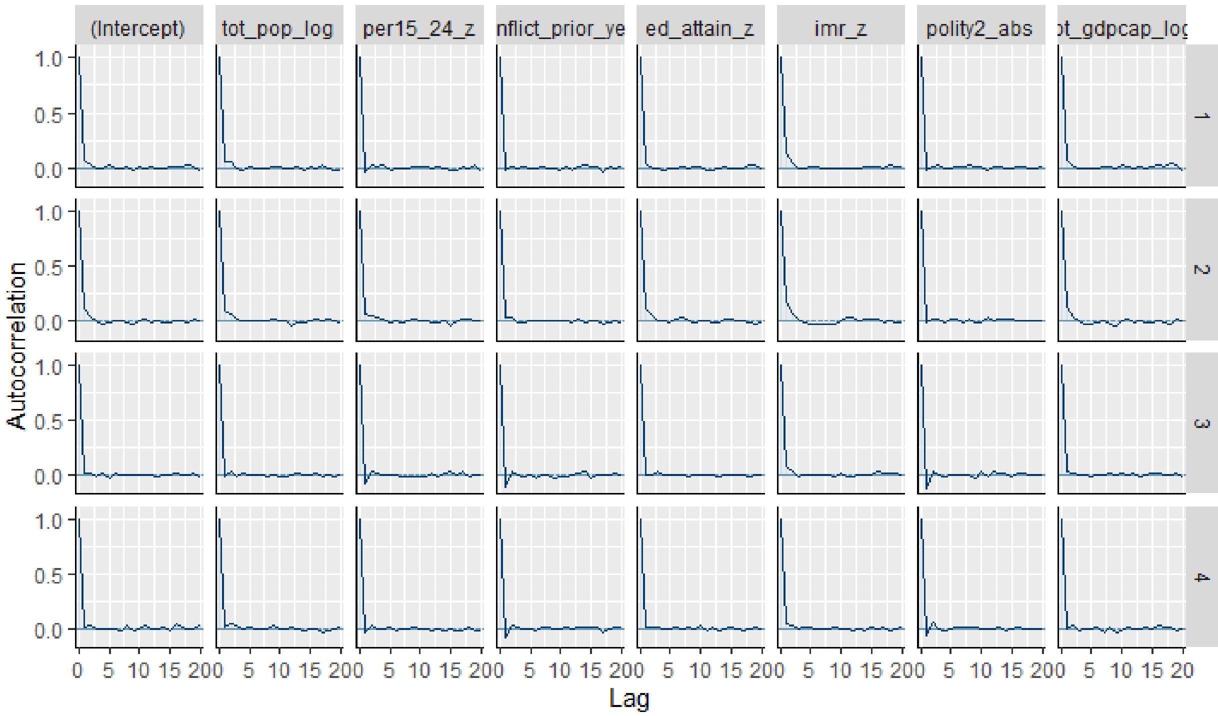

Figure C3 – MCMC lag plots for global conflict occurrence model parameters

Appendix D

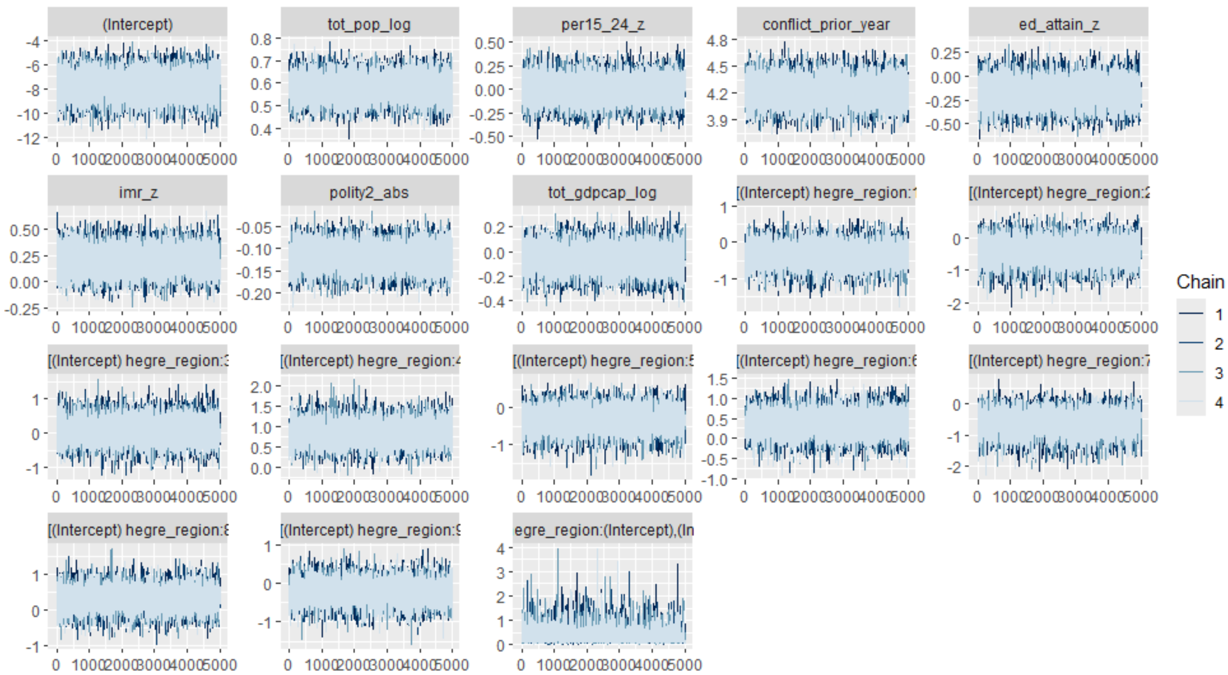

Figure D1 – MCMC trace plots for multilevel varying-intercepts conflict occurrence model parameters

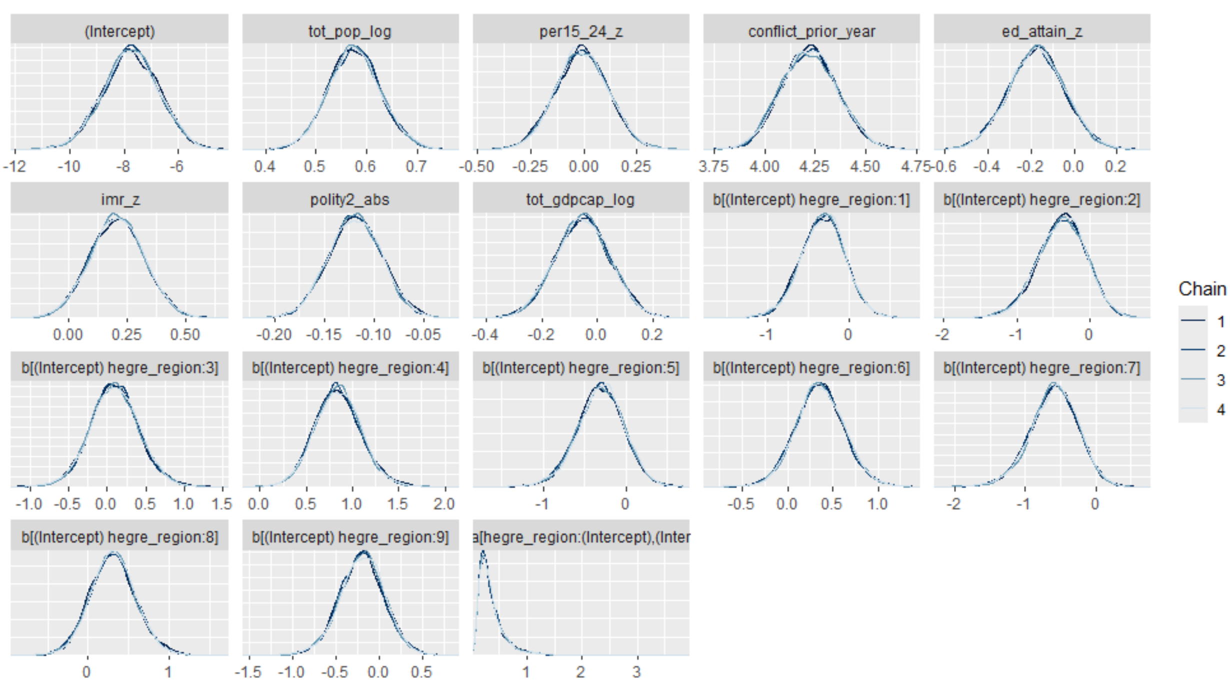

Figure D2 – MCMC density plots for multilevel varying-intercepts conflict occurrence model parameters

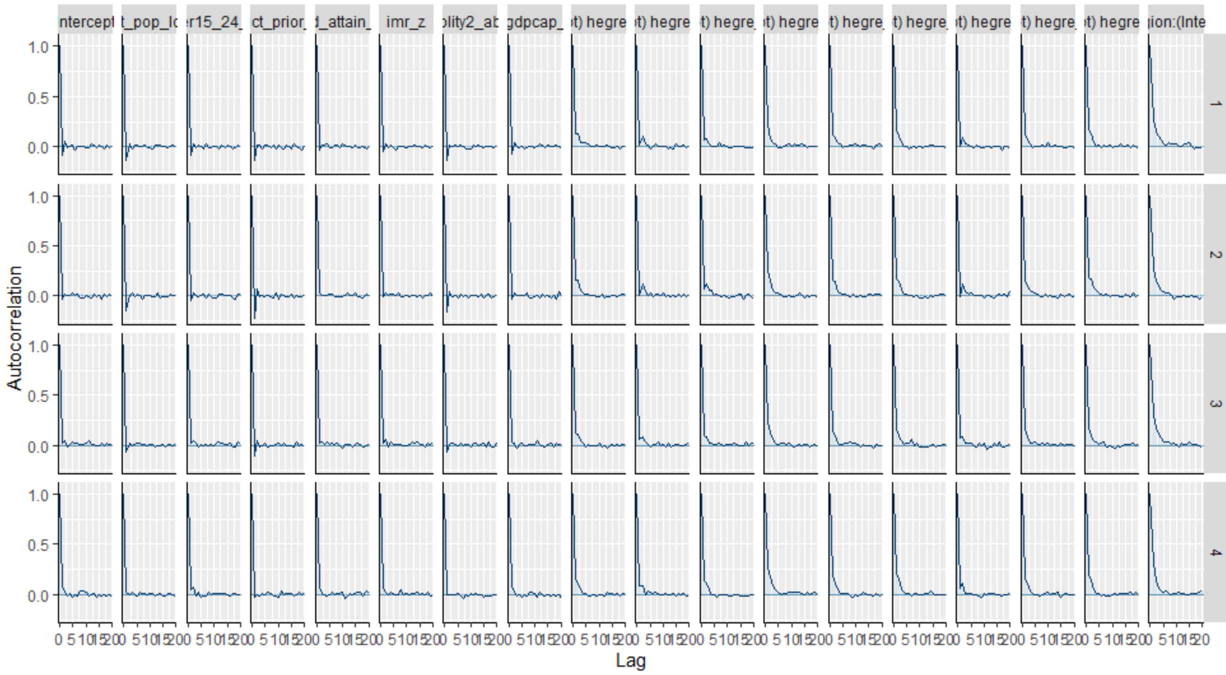

Figure D3 – MCMC trace plots for multilevel varying-intercepts conflict occurrence model parameters

References

Alley, J. (2023, October 30). Using Hierarchical Models to Estimate Heterogeneous Effects. *SocArXiv*. https://doi.org/10.31235/osf.io/2e9zh

Apolte, T., & Gerling, L. (2018). Youth bulges, insurrections and labor-market restrictions. *Public Choice*, 175(1/2), 63–93. https://www.jstor.org/stable/48719976

Bidyuk, P., Gozhvi, A., & Kalinina, I. (2018). Modeling Military Conflicts Using Bayesian Networks. *2018 IEEE First International Conference on System Analysis & Intelligent Computing (SAIC)*, 1-6, https://doi.org/10.1109/SAIC.2018.8516861

Collier, P., Elliot, L., Hegre, H., Hoeffler, A., Reynal-Querol, M., & Sambanis, N. (2003). *Breaking the Conflict Trap. Civil War and Development Policy*. Oxford: Oxford University Press.

Collier, P. (2007). *The Bottom Billion. Why the Poorest Countries are Failing and What Can Be Done About It*. Oxford: Oxford University Press.

Collier, P., Hoeffler, A. & Soderbom, M. (2008). Post-conflict risks. *Journal of Peace Research* 45(4), 461-478. https://www.jstor.org/stable/27640710

Davies, S., Pettersson, T., & Öberg, M. (2023). Organized violence 1989–2022, and the return of conflict between states. *Journal of Peace Research*, 60(4), 691-708. https://doi-org.ezproxy.cul.columbia.edu/10.1177/00223433231185169

Esty, D., Goldstone, J., Gurr, T., Harff, B., Levy, M., Dabelko, G., Surko, P., & Unger, A. (1998). *State Failure Task Force Report: Phase II Findings*. McLean VA: Science Applications International, for State Failure Task Force.

Fearon, J. D., & Laitin, D. D. (2003). Ethnicity, Insurgency, and Civil War. *The American Political Science Review*, 97(1), 75–90. http://www.jstor.org/stable/3118222

Feenstra, R. C., Inklaar, R., & Timmer, M. P. (2015). The Next Generation of the Penn World Table. *American Economic Review*, 105(10), 3150-3182. www.ggdc.net/pwt

Flückiger, M., & Ludwig, M. (2018). Youth Bulges and Civil Conflict: Causal Evidence from Sub-Saharan Africa. *The Journal of Conflict Resolution*, 62(9), 1932–1962. https://www.jstor.org/stable/48596881

Gelman, A., Hill, J., & Vehtari, A. (2021). *Regression and Other Stories*. Cambridge University Press. https://avehtari.github.io/ROS-Examples/

Gleditsch, N. P., Wallensteen, P., Eriksson, M., Sollenberg, M., & Strand, H. (2002). Armed Conflict 1946-2001: A New Dataset. *Journal of Peace Research*, 39(5), 615–637. http://www.jstor.org/stable/1555346

Gleditsch, K. S. (2007). Transnational Dimensions of Civil War. *Journal of Peace Research*, 44(3), 293–309. http://www.jstor.org/stable/27640512

Goldstone, J. A. (2002). Efflorescences and Economic Growth in World History: Rethinking the "Rise of the West" and the Industrial Revolution. *Journal of World History*, 13(2), 323–389. http://www.jstor.org/stable/20078976

Goodrich, B., Gabry, J., Ali, I., & Brilleman, S. (2019). rstanarm: Bayesian applied regression modeling via Stan. R package version 2.32.1. mc-stan.org/rstanarm

Hegre, H., Ellingsen, T., Gates, S., & Gleditsch, N.P. (2001). Toward a Democratic Civil Peace? Democracy, Political Change, and Civil War, 1816-1992. *American Political Science Review* 95:33-48. https://www.jstor.org/stable/3117627

Hegre, H., & Sambanis, N. (2006). Sensitivity Analysis of Empirical Results on Civil War Onset. *The Journal of Conflict Resolution*, 50(4), 508–535. http://www.jstor.org/stable/27638504

Hegre, H., Karlsen, J., Nygård, H. M., Strand, H., & Urdal, H. (2013). Predicting Armed Conflict, 2010–2050. *International Studies Quarterly*, 57(2), 250–270. http://www.jstor.org/stable/24016137

Hegre, H.; Nygård, H. M., & Landsverk, P. (2021) Can We Predict Armed Conflict? How the First 9 Years of Published Forecasts Stand Up to Reality. *International Studies Quarterly*, 65(3), 660–668. https://doi.org/10.1093/isq/sqaa094

Higashijima, M., & Houle, C. (2018). Ethnic Inequality and the Strength of Ethnic Identities in Sub-Saharan Africa. *Political Behavior*, 40(4), 909–932. https://www.jstor.org/stable/48694154

Johnson, A., Ott, M. Q., & Dogucu, M. (2021). *Bayes Rules! An Introduction to Applied Bayesian Modeling*. CRC Press. https://www.bayesrulesbook.com/

Jones, Z. M., & Lupu, Y. (2018). Is There More Violence in the Middle? *American Journal of Political Science*, 62(3), 652–667. http://www.jstor.org/stable/26598773

Kahl, C. H. (2006). *States, Scarcity, and Civil Strife in the Developing World*. Princeton University Press. https://doi.org/10.2307/j.ctv36zrx1

LaGraffe, D. (2012). The Youth Bulge in Egypt: An Intersection of Demographics, Security, and the Arab Spring. *Journal of Strategic Security*, 5(2), 65–80. http://www.jstor.org/stable/26463960

Palik, J., Obermeier, A. M., & Rustad, S. A. (2022) Conflict Trends: A Global Overview, 1946–2021. *PRIO Paper*. Oslo: PRIO. https://www.prio.org/publications/13178

Tezcür, G. M. (2016). Ordinary People, Extraordinary Risks: Participation in an Ethnic Rebellion. *The American Political Science Review*, 110(2), 247–264. http://www.jstor.org/stable/24809521

The World Bank, World Development Indicators (2024). GDP per capita, International Comparison Program [Data file]. Retrieved from https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD

Thyne, C. L. (2006). ABC's, 123's, and the Golden Rule: The Pacifying Effect of Education on Civil War, 1980-1999. *International Studies Quarterly*, 50(4), 733–754. http://www.jstor.org/stable/4092777

United Nations (2022). World Population Prospects 2022: Data Sources. Department of Economic and Social Affairs, Population Division. (UN DESA/POP/2022/DC/NO. 9).

Urdal, H. (2004). The devil in the demographics: The effect of youth bulges on domestic armed conflict, 1950–2000. *World Bank Social Development Papers*, No. 14. http://documents.worldbank.org/curated/en/794881468762939913/The-devil-in-the-demographics-the-effect-of-youth-bulges-on-domestic-armed-conflict-1950-2000

Urdal, H. (2005). People vs. Malthus: Population Pressure, Environmental Degradation, and Armed Conflict Revisited. *Journal of Peace Research*, 42(4), 417–434. http://www.jstor.org/stable/30042334

Urdal, H. (2006). A Clash of Generations? Youth Bulges and Political Violence. *International Studies Quarterly*, 50(3), 607–629. http://www.jstor.org/stable/4092795

Urdal, H., & Hoelscher, K. (2012). Explaining Urban Social Disorder and Violence: An Empirical Study of Event Data from Asian and Sub-Saharan African Cities. *International Interactions*, 38(4), 512–528. https://doi.org/10.1080/03050629.2012.697427

Wimmer, A., Cederman, L.-E., & Min, B. (2009). Ethnic Politics and Armed Conflict: A Configurational Analysis of a New Global Data Set. *American Sociological Review*, 74(2), 316–337. http://www.jstor.org/stable/27736063

Yair, O., & Miodownik, D. (2016). Youth bulge and civil war: Why a country's share of young adults explains only non-ethnic wars. *Conflict Management and Peace Science*, 33(1), 25-44. https://doi-org.ezproxy.cul.columbia.edu/10.1177/0738894214544613