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# On climate and conflict: Precipitation decline and communal conflict in Ethiopia and Kenya

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**Abstract**

This study exploits a sudden and abrupt decline in precipitation of the long rains season in the Horn of Africa to analyze the possible link between climate change and violent armed conflict. Following the 1998 El Niño there has been an overall reduction in precipitation levels – associated with sea-surface temperature changes in the Indian and Pacific Oceans – resulting in an increase in the number and severity of droughts. Given that the probable cause of this shift is anthropogenic forcing, it provides a unique opportunity to study the effect of climate change on society compared to statistical inference based on weather variation. Focusing on communal conflict in Ethiopia and Kenya between 1999 and 2014, exploiting cross-sectional variation across districts, the regression analysis links the precipitation decline to an additional 1.3 conflict events per district. The main estimates show that there is a negative correlation between precipitation and communal conflict with a probability of 0.90. Changing model specification to consider plausible alternative models and accommodate other identifying assumptions produces broadly similar results. The generaliziability of the link between precipitation decline and conflict breaks down when using out-of-sample cross-validation to test the external validity. A leave-one-out cross-validation exercise shows that accounting for climate contributes relatively little to improving the predictive performance of the model. This suggests that there are other more salient factors underlying communal violence in Ethiopia and Kenya. As such, in this case the link between climate and conflict should not be overstated.

**Keywords**

climate change, communal conflict, cross-validation, Ethiopia, Kenya, precipitation

## Introduction

Despite a growing and productive literature on climate change and conflict, the possible nexus remains speculative due to inconclusive results (Klomp & Bulte, 2013; Theisen, Gleditsch & Buhaug, 2013).[1] An important shortcoming of existing work, which this study aims to overcome, is that most research conflates climate variability with climate change (Buhaug, 2015). Using inter- or intra-annual weather variation might not be a suitable climate change proxy (Selby, 2014). Although exploiting relatively high-frequency data can provide information on conflict seasonality (Witsenburg & Adano, 2009; Ember et al., 2012, 2014) or weather's strategic importance (Carter & Veale, 2014), a major limitation is the implicit assumption that weather variation has an almost immediate impact on conflict risk. Whereas using more fine-grained spatial data can help account for subnational variation in climatic conditions (e.g O'Loughlin et al.,

[1] Bernauer, Böhmelt & Koubi (2012), Gleditsch (2012) and Scheffran et al. (2012) also find no consensus in contrast with Hsiang, Burke & Miguel (2013) and Hsiang & Burke (2014). Hsiang, Burke & Miguel (2013) claim to find causal evidence linking climatic events to human conflict, but these results have been contested (Buhaug et al., 2014) (see also Hsiang, Burke & Miguel, 2014). Others have shown that climatic conditions can be linked to conflict, but its salience is often limited (O'Loughlin et al., 2012; Ayana et al., 2016; von Uexkull et al., 2016).

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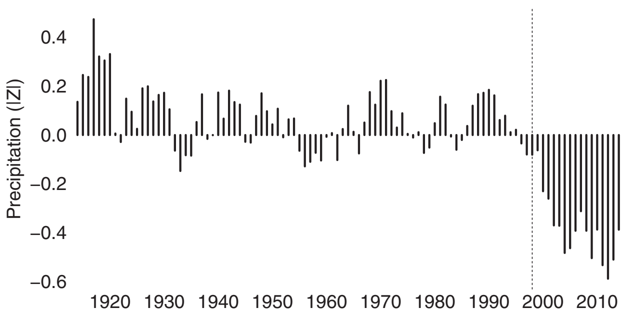


Figure 1. 15-year moving average precipitation anomaly long rains season (March–June) 1915–2014

Aggregate for Ethiopia and Kenya. Precipitation anomalies are calculated by subtracting the mean and dividing by the standard deviation of the sample (1900–2014): $(p_t - \bar{p})/\sigma_p$. Data from CenTrends (Funk et al., 2015).

2012; O'Loughlin, Linke & Witmer, 2014; von Uexkull, 2014; Maystadt & Ecker, 2014; Maystadt, Calderone & You, 2015), this doesn't necessarily apply to the temporal scale. So while current empirical models can help identify the effect of climate variability on conflict (Nordkvelle, Rustad & Salmivalli, 2017), they arguably provide scant information on the effects of climate change.

Therefore, rather than relying on variation this study exploits a quasi-natural experiment for identification: a sudden and abrupt precipitation shift in the long rains season in the Horn of Africa following the 1998 El Niño. Increases in sea-surface temperatures in the south-central Indian Ocean and west Pacific Ocean have been linked to a precipitation decline in eastern Africa (Funk et al., 2008; Williams & Funk, 2011; Williams et al., 2012; Lyon & Dewitt, 2012; Lott, Christidis & Stott, 2013; Lyon, 2014; Rowell et al., 2015) resulting in an increase in the number and severity of droughts in this region (Funk, 2012; Lyon, 2014). Figure 1 illustrates this decline, plotting the region's 15-year moving average of the standardized precipitation anomaly. It shows that in the past two decades precipitation levels have been significantly lower. This decline has come as a surprise as most climate models predicted an increase for East Africa (Rowell et al., 2015) and has been dubbed the 'East African climate paradox'. An important question is whether this decline is due to anthropogenic forcing or natural variability. Some suggest the latter (Lyon, 2014; Yang et al., 2014), in which case this is an exceptional event with no recent precedent in the last 100 years, as illustrated by Figure 1. Although such an event cannot be ruled out as cause (Rowell et al., 2015), there is a preponderance of evidence pointing to human-induced climate change as the main cause (Williams & Funk, 2011; Lott, Christidis & Stott, 2013; Rowell et al., 2015), possibly alongside other drivers such as variability (Liebmann et al., 2014; Rowell et al., 2015).

In contrast to inferences based on weather variation, this decline provides a better opportunity to examine the effect of climate change on conflict risk, given its abrupt and possibly permanent nature (Lyon & Dewitt, 2012),[2] thereby also overcoming limitations of other quasi-natural experiments such as using the El Niño cycle (Hsiang, Meng & Cane, 2011).[3]

This study focuses on the link between the precipitation decline and communal conflict in Ethiopia and Kenya between 1999 and 2014. Agriculture is the dominant economic sector in both countries; as such they are vulnerable to adverse changes in local climate. These changes possibly reduce coping capabilities of people living in vulnerable environments where livelihoods depend on factors such as precipitation (Holmgren & Öberg, 2006). Communal conflict is commonly linked to climate as there are fewer constraints in engaging in violence with other groups compared to the state (Fjelde & von Uexkull, 2012; Theisen, 2012). Both Kenya and Ethiopia are harried by this conflict type having caused a reported 2,700 and 3,480 fatalities between 1999 and 2014 in each country, respectively.[4] These conflicts often involve violent confrontations concerning access to natural resources such as water or pasture. For example, the Afar, a pastoralist group in eastern Ethiopia, often clash with neighbouring groups, both sedentary farmers and mobile pastoralists, over water, exclusive claims on grazing land, and access routes. These clashes tend to be more frequent during droughts, for instance with the Ise Somali, a competing pastoralist group (Markakis, 2003). In another example, in February 2017 in Laikipia, Kenya, an estimated 10,000 herders caused havoc in search of pasture for their herds clashing with the local population.

Concerning farmer–herder conflicts in Africa's semi-arid regions, Hussein, Sumberg & Seddon (1999) note that alleged increases in conflict are partially due to

[2] For examples of studies exploiting variation in climate over the long term see Zhang et al. (2007) and Tol & Wagner (2009).

[3] To estimate the impact of climate on civil conflict, Hsiang, Meng & Cane (2011) use El Niño years as a treatment and La Niña years as control, assuming that societies respond differently to the global climate in these two states. However, this ignores the fact that these societies have developed adaptive livelihood strategies. In contrast this study exploits a seemingly permanent shift.

[4] Based on data from Sundberg & Melander (2013).

(i) changing resource use patterns and the associated increased competition, and (ii) a breakdown of traditional mechanisms managing both resource use and conflict.[5] Seter, Theisen & Schilling (2018) also point to the importance of national-level processes. Explaining these conflicts in the context of climate change, the Malthusian model is often invoked. Here agents compete over a prize, for example pasture, that becomes more valuable due to climate-change induced scarcity and violence becomes the dominant strategy to capture said prize. Olsson (2016) shows that climate and conflict can also be linked through market disintegration. A climate-change induced decrease in availability over a common resource could lead to trade reductions between groups competing over access to the resources, making the groups' welfare independent of each increasing conflict risk.[6]

There is a well-established literature on climate and conflict in East Africa. For Kenya, Theisen (2012) found that violence levels were higher following years with below-average precipitation; Detges (2014) shows that pastoralist violence occurs more commonly near well sites and locations with higher precipitation levels in northern Kenya; and Raleigh & Kniveton (2012) link higher rates of communal conflict with anomalous wet periods for Kenya and Ethiopia.[7] Related, Maystadt & Ecker (2014) and Maystadt, Calderone & You (2015) show that conflict is associated with higher temperatures in Somalia and Sudan. In contrast, other studies have illustrated that climatic conditions tend to be moderate conflict predictors (Rowhani et al., 2011; O'Loughlin et al., 2012; O'Loughlin, Linke & Witmer, 2014; Ayana et al., 2016).

Compared to the existing literature this study makes two contributions. First, to the best of my knowledge, this is the first study examining the effect of – contemporary – climate change on conflict, rather than relying on a proxy based on climate variability. Kevane & Gray (2008) exploit long-term changes in local climate for Darfur, while Adano et al. (2012) use long-term historical data for the Marsabit and Narok districts in Kenya. The analysis presented in this study arguably provides a clearer example of the effect of climate change by exploiting this abrupt precipitation decline while also covering a larger area. Second, this study contributes by using a more comprehensive precipitation dataset, overcoming limitations that might have hampered existing studies. The commonly used climatologies suffer possibly from measurement error due to a decline in the number of precipitation measurement stations since 2000 (Funk et al., 2015), which is problematic as most studies focus on the years after 2000, resulting in a possible bias. The dataset used for this study (CenTrends; Funk et al., 2015) overcomes these issues, as described in more detail in the data section.

The regression analysis shows that between 1999 and 2014, conflict levels have been higher in districts experiencing larger precipitation declines of the long rains season. The results also highlight a strong correlation between pastoralism and communal conflict, but surprisingly the effect of the precipitation decline is not different in districts with substantial shares of pastoralist areas compared to others. The estimates also show a negative link between precipitation and civil conflict, while the results are not robust including lower-intensity events such as riots. Testing the external validity of the results, predicting the outcome for left-out districts shows that excluding precipitation from the econometric model has a negligible effect on the model's predictive power, regardless of estimation method, thereby reflecting previous findings that temper the salience of climatic conditions in explaining conflict (O'Loughlin et al., 2012; O'Loughlin, Linke & Witmer, 2014; Wischnath & Buhaug, 2014; Ayana et al., 2016).

## Data and measurement

Districts are used as unit-of-analysis, which is the smallest subnational unit at which the conflict data can be reasonably accurately located (Weidmann, 2015), and they are intuitive, capturing heterogeneity following subnational boundaries (Østby, Nordås & Rød, 2009; Aas Rustad et al., 2011; Greiner, 2013), which is important in the context of Ethiopia and Kenya. Fixed boundaries for 1999 are used taken from FAO's GAUL dataset.

### *Precipitation*

Precipitation data are taken from CenTrends, which provides high-quality estimates for East Africa, available on a 0.1° grid for 1900–2014 (Funk et al., 2015). In constructing CenTrends, particular attention has been given to years since 2000. A reduction in measurement stations resulted in a paucity of actual observations and inhomogeneous monitoring network. To overcome these limitations, data from various station archives were

[5] For studies on the role of institutions see Adano et al. (2012), Eck (2014) and Linke et al. (2015).

[6] For this study, this particular theory cannot be tested due to data constraints.

[7] For a discussion on the results by Theisen (2012) see Miguel, Hsiang & Burke (2014) and Theisen (2014).

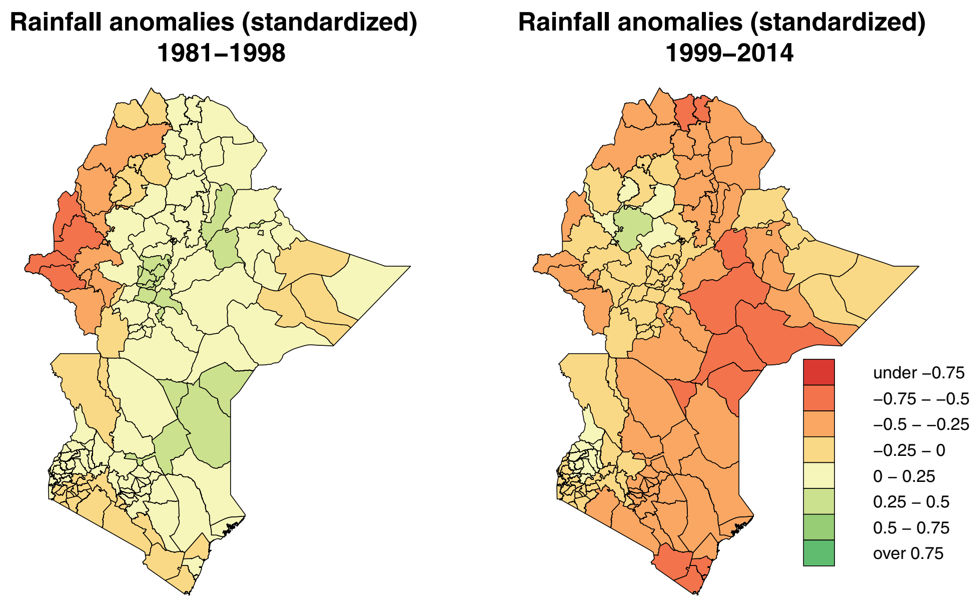


Figure 2. Average rainfall anomaly per district in Ethiopia and Kenya between 1981/98 and 1999/2014

combined and coverage gaps filled with data from nearby stations or additional data from national meteorological agencies. Remaining missing values were imputed using spatial kriging, accounting for station-specific measurement error, described in more detail by Funk et al. (2015). As such, CenTrends provides the most comprehensive precipitation climatology for East Africa currently available.

The effect of climate change is estimated exploiting a shift in precipitation levels of the long rains season between March and June. Following Pricope et al. (2013), the period 1981–98 is used as benchmark to which precipitation levels between 1999 and 2014 are compared (see also Figure A1 in the Online appendix). For each individual district (N = 155) the average anomaly is calculated and the difference between the 'treated' and benchmark period is used as a measure for climate change.

Figure 2 illustrates variation across districts showing an increase in aridity over the past 15 years in an already arid region. The decline in precipitation levels has been more pronounced in the eastern part of the region, such as in the Ethiopian highlands and northern Kenya – both important agricultural regions relying on farming (Ethiopia) and pastoralism (Kenya).

*Conflict data*

The Uppsala Conflict Data Programme Georeferenced Event Dataset (GED v.5.0; Sundberg & Melander, 2013) is used for conflict data. This dataset contains detailed information from 1989 onwards on the location, timing, and severity of conflict events, along with information on the warring parties involved. This is the most comprehensive conflict event dataset publicly available and is superior to others in terms of geocoding precision (Eck, 2012) and accuracy of included events (Weidmann, 2013, 2015).

An important caveat of the dataset is that it only includes events associated with a conflict that has reached a fixed fatality threshold of 25 battle-related deaths in a single year (Croicu & Sundberg, 2015). This entails that certain conflict types, or parts of the conflict process, are not covered – for example riots, strikes, or protests. This means that the estimation results won't account for more incidental violence at lower intensity levels. In addition, a large part of the dataset is compiled from media sources which could introduce reporting bias; however, Croicu & Kreutz (2016) have shown that this possible bias is very small.

Some observations are excluded: those that (i) cannot be accurately located at district level, (ii) are non-unique events, and (iii) are theoretically irrelevant. The latter includes military actions on Ethiopian or Kenyan territory conducted by the army of neighbouring countries, for example, events related to the Ugandan army pursuing elements of the Lord's Resistance Army that have crossed the border. The main analysis focuses exclusively on the incidence of communal conflicts, which are conflicts taking place along lines of communal identity such as an ethnic group (Petterson, 2014).

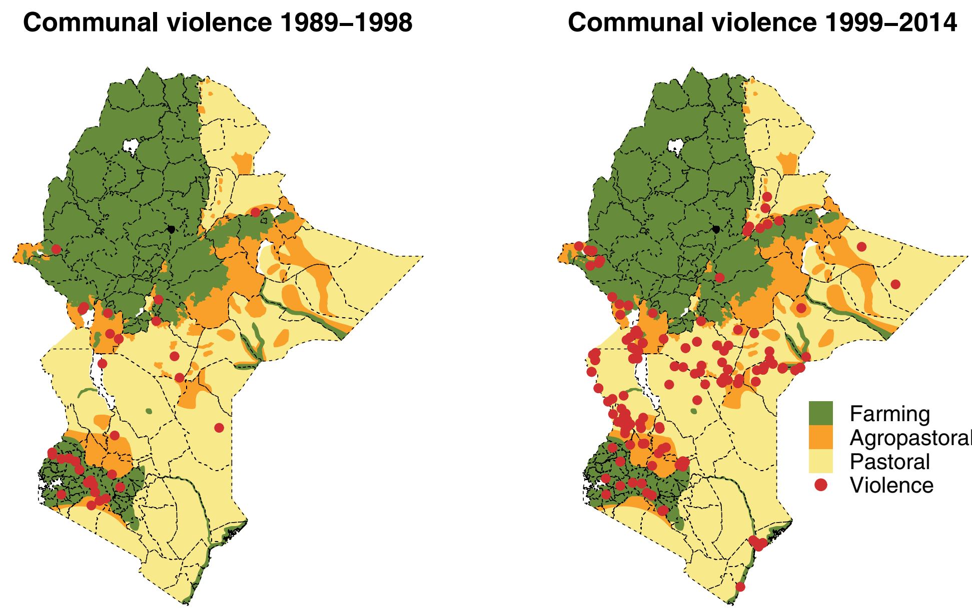


Figure 3. Location of individual communal violence events in Ethiopia and Kenya between 1989/98 and 1999/2014
Livelihood zones capture the dominant livelihood strategy within area. Data from UCDP, FEWS Net.

Figure 3 plots conflict event locations along with district boundaries (dashed lines) and livelihood zones. Livelihood zone boundaries are taken from the Famine Early Warning System Network (FEWS Net). A livelihood zone is defined as 'an area where people generally rely on the same options to obtain food and income and engage in trading'. As such, households within these zones likely react similarly to local climate changes due to similarities in their livelihood strategies. Three types of zone are included: (i) pastoral, (ii) agropastoral and (iii) farming.

Figure 3 illustrates that between 1989 and 1998, communal conflict was mainly concentrated in southwestern Kenya and some spots in southern Ethiopia. Since 1999 this conflict type has become more widespread, covering western Kenya, central Ethiopia and the pastoral border region between the two countries. Various conflict events occur along the borders of different livelihood zones, which might indicate some level of animosity between people relying on different agricultural activities for their subsistence and income.[8] Most communal conflicts involve members of different ethnic groups. Examples include a confrontation in 2003 between the Afar and Ise in the Afar region in Ethiopia which killed an estimated 40 people, or in 2006 a battle in northern Kenya between Ethiopian and Kenyan nomads, leaving 38 people dead.

## Estimation framework

The estimation exploits cross-sectional variation in the precipitation shift across 155 districts to estimate the effect of climate change on communal conflict levels. The statistical model has the following functional form:

$$y_j = \alpha + \delta \Delta p_j + \beta y_{1989-98} + \rho \sum_k W_{jk} y_k. \quad (1)$$

Outcome variable $y_j$ is a count of the number of communal conflict events in a district between 1999 and 2014 which is linked to the precipitation shift $\Delta p_j$ which is measured as the difference in the average anomaly, subtracting the benchmark period (1981–98) average from the 1999–2014 average, similar to a long differences approach (Burke & Emerick, 2016). Since conflicts tend to be persistent over time and display spatial interdependence (Buhaug & Gleditsch, 2008), it is pivotal to control for conflict dynamics to isolate the climate change effect. Therefore, the model includes the temporal lag of the outcome variable ($y_{1989-98}$), the number of conflict events between 1989 and 1998. The spatial lag $\sum_k W_{jk} y_k$ deals with possible spillover effect and is constructed as the sum of the outcome variables in the $k$ neighbouring districts, irrespective of national borders

[8] For a broader discussion on social vulnerability to climate change, see Otto et al. (2017).

between the two countries, since these tend to be porous.[9]

A shortcoming of the estimation framework is that it is a reduced-form model, similar to Couttenier & Soubeyran (2014), where the impact of climate change on conflict is estimated directly, rather than examining specific channels. Ideally we would like to examine possible mechanisms, but unfortunately, due to the timing of the shift exploited in this study, there are constraints regarding data availability, for example local commodity prices. Nonetheless, the reduced-form model still provides valuable insights concerning the impact of climate change and complements existing case studies.

The distribution of the outcome variable, the count of conflict events, is overdispersed ($\mu = 1.5$, $\sigma = 34.2$) with 21.9% non-zero observations. Therefore, a negative binomial distribution is used to account for overdispersion (Hausman, Hall & Griliches, 1984; Lloyd-Smith, 2007). Using count data one would prefer to use a Poisson model, but given that the variance exceeds the mean, such a model would fit the data poorly. The parameters are estimated using Bayesian inference which has the advantage of producing consistent estimates in the presence of spatial dependence; the model is fitted using a type of Markov Chain Monte Carlo algorithm, the Gibbs sampler (JAGS; Plummer, 2014), where the conditional distribution of spatial parameter $\rho$ can be integrated out solving the issue of multiple integration in the Bayesian setting (LeSage, 1997).[10] A practical advantage is the intuitive probabilist interpretation of the estimated posterior distribution, in contrast with standard confidence intervals. This provides better insights into the uncertainty associated with the estimates.[11] Diffuse, or non-informative, priors are used for the model's parameters ($N(0{,}10)$), which means that the estimates will be similar to those obtained by maximum likelihood estimation (Gelman et al., 1995). The regression results will be scrutinized using leave-one-out cross validation (LOO), details for which will be discussed in the relevant section.

[9] The adjacency matrix is not row-standardized: this would imply that conflict diffusion is larger for districts with fewer neighbors, which is not theoretically justifiable. Regardless, the adjacency matrix specification should have little effect on the estimated effect (LeSage & Pace, 2014).

[10] See also Ward & Gleditsch (2002).

[11] Throughout this article the uncertainty classifications are based on Mastrandrea et al. (2010): 33%–66%, about as likely as not; 66%–100%, likely; 90%–100%, very likely; 99%–100%, virtually certain.

## Results

### *Empirical regularities*

Before fitting the regression model the empirical regularities in the data for 1990–2014 are analyzed. Using a 15-year moving average of the precipitation anomaly ($p_{jt}$), the data show that for the benchmark period (1981–98) the probability of a drought in a given district year ($p_{jt} < 0$) is 0.52 and 0.14 for a severe drought ($p_{ij} \leq -1$). These probabilities are representative for the whole sample (1900–2014): 0.53 and 0.15, respectively. Since 1998 there has been a substantial increase however, by eight points for droughts (0.60) and 11 for severe droughts (0.25). This means that the frequency of a severe drought has increased from one in seven to one in four years on average, reflecting other analyses (Funk, 2012; Rowell et al., 2015).

To test how drought severity relates to communal conflict, I follow Blomberg & Hess (2002) and estimate the conditional probability, again using the 15-year moving average. Specifically, I estimate conflict probability per district-year conditional on the moving average being below a value on the $[-0.6; 0.6]$ interval (Figure 4). Between 1990 and 2014, 3% of district-years experienced communal conflict ($N = 3,875$). This probability gradually increases when precipitation levels recede, peaking at 0.06. There is a plateau above 0.05 when the 15-year average precipitation anomaly is between –0.55 and –0.20. Considering conflict probability conditional on severe drought, $Pr(y_{jt}|p_{jt} \leq -1)$, there is a relatively large increase from 0.01 between 1990 and 1998 to 0.06 between 1998 and 2014 (see also Table A1 in the Online appendix). The data thus show that (i) severe droughts have become more common and (ii) the probability of conflict conditional on these droughts has increased.

### *Regression analysis*

Table I presents the main estimation results. The baseline model, including only information on conflict dynamics (column 1), highlights the persistence of conflict over time and space. Moving from low to high past conflict levels is associated with a 0.9 increase in the log count of the outcome variable, corresponding to 2.5 events (sample average is 1.5 events). A similar increase in the spatial lag shows a 2.2 increase in the outcome variable, or nine events. The model specification in column 2 includes the variable accounting for the shift in precipitation levels of the long rains seasons between 1981–98 and 1999–2014. The estimate shows a negative correlation, with a 50% uncertainty interval (UI) ranging from –1.5 to –0.9, linking precipitation decline

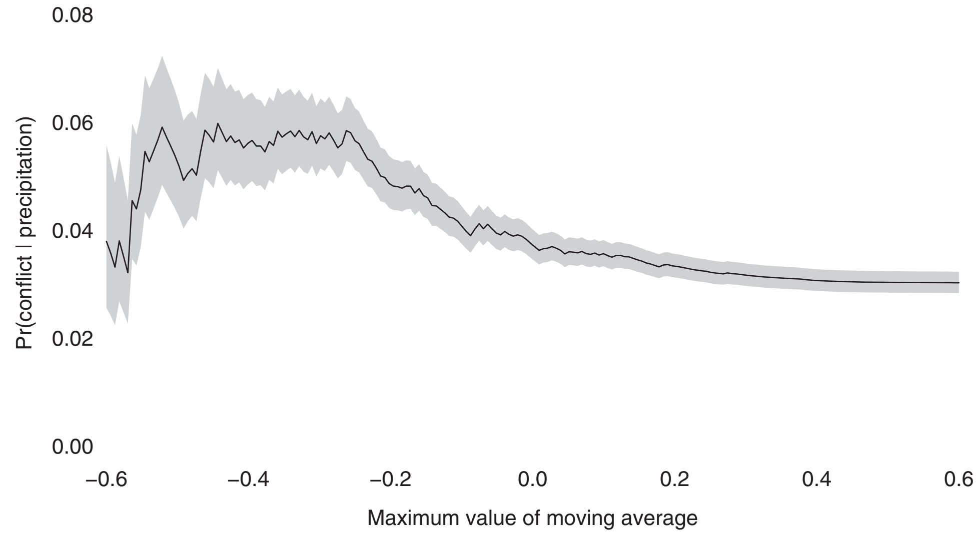


Figure 4. Conditional probability of communal violence at different thresholds of 15-year precipitation anomaly moving average, covering all district-years 1990–2014 ($N = 3,875$)

Grey-shaded area represents 50% uncertainty interval.

Table I. Predicting communal conflict in district *j*, 1999–2014 ($N = 155$)

| | | | *Number of events* | | | | *Battle-related fatalities* | |
|---|---|---|---|---|---|---|---|---|
| *Specification* | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* | *(8)* |
| ΔRain | | –1.2 | –0.6 | | –1.5 | –0.6 | –0.3 | |
| | | (–2.1; –0.4) | (–1.4; 0.3) | | (–3.1; –0.1) | (–1.7; 0.4) | (–1.9; 1.0) | |
| BEST | | | | 1 | | | | 1 |
| | | | | (–1; 4) | | | | (–4; 5) |
| Violence$^{1989–98}$ | 0.9 | 1.1 | 1.2 | 1.2 | 1.1 | 1.3 | 3 | 2 |
| | (0.1; 2.4) | (0.3; 2.5) | (0.5; 2.4) | (0.4; 2.4) | (0.3; 2.4) | (0.5; 2.6) | (0; 9) | (0; 8) |
| Violence$^{neighbours}$ | 2.2 | 2.6 | 1.7 | 1.7 | 2.5 | 1.8 | 2 | 2 |
| | (1.1; 3.8) | (1.6; 3.9) | (0.7; 3.0) | (0.6; 3.1) | (1.5; 3.8) | (0.6; 3.3) | (0; 6) | (0; 6) |
| Population density | | | –1 | –1 | –1 | | –3 | –3 |
| | | | (–3; 2) | (–4; 2) | (–4; 2) | | (–8; 3) | (–9; 3) |
| Pastoral area | | | 1.6 | 1.7 | | 1.6 | 2 | 2 |
| | | | (0.4; 2.8) | (0.5; 2.8) | | (0.2; 3.0) | (0; 4) | (0; 4) |
| ΔRain*population density | | | | | –3 | | | |
| | | | | | (–17; 9) | | | |
| ΔRain*pastoral area | | | | | | 0 | | |
| | | | | | | (–1.9; 1.9) | | |
| Intercept | –0.2 | –0.5 | –1.1 | –2.0 | –0.5 | –1.1 | 1.5 | 1 |
| | (–0.7; 0.3) | (–1.0; 0) | (–1.7; –0.4) | (–3.6; –0.4) | (–1.1; 0) | (–1.7; –0.4) | (0.6; 2.7) | (–2; 4) |
| Deviance | 333 | 325 | 319 | 321 | 326 | 319 | 520 | 520 |
| DIC | 337.8 | 331.0 | 328.1 | 328.8 | 333.7 | 328.2 | 528.8 | 529.0 |

The table presents mean estimated effect; 95% UI given in parentheses. Estimates are based on three chains with 2,500 iterations each, the first 1,000 of which are discarded as 'burn-in'. All input variables are placed on a common scale by subtracting the mean and dividing by twice the standard deviation, except for *Pastoral area* which is a binary indicator for districts where pastoralism is the dominant livelihood strategy for at least 25% of district area and BEST which is measured on the unity interval. Standardized coefficients can be interpreted as the effect of moving from low to high values (Gelman, 2008). DIC (deviance information criterion) is an estimate of the expected predictive error (lower deviance is better) (Plummer, 2014).

to increased levels of communal conflict at district level. The coefficient's sign is almost certainly negative with a probability of 0.999. The mean of the posterior distribution indicates that a two-standard deviation increase in precipitation reduces the outcome variable's log count by 1.2, similar to the magnitude of the temporal lag. Given the average precipitation decline of about 0.25 standard deviations, this corresponds to 1.3 additional conflict events per district between 1999 and 2014.

To account for other theoretically relevant factors, variables for population density and pastoralism are included in the model. Conflict risk is commonly linked to population size (Hegre & Sambanis., 2006; Urdal, 2011) as it increases the potential pool of agents willing to engage in violence under adverse conditions; moreover, larger populations put additional pressure on available resources, which might culminate in violence. Including population density shows that more densely populated districts are linked to lower conflict levels.[12] This result could be due to (i) densely populated districts having higher levels of economic specialization, making them less dependent on agriculture, the sector most affected by precipitation, for their income, or (ii) sparsely populated districts being more remote and having higher conflict levels due to absence of the state (Adano et al., 2012). Interacting the population variable with precipitation (column 5) shows a large negative effect for more densely populated districts, but this estimate comes with a wide uncertainty interval.

A number of studies have highlighted the prevalence of violence in pastoralist societies in Ethiopia and Kenya (Hagmann & Mulugeta, 2008; Greiner, 2013; Zefferman & Mathew, 2015), while others discussed possible links with environmental conditions (Gray et al., 2003; Meier, Bond & Bond, 2007; Schilling, Opiyo & Scheffran, 2012; Ember, Adem & Skoggard, 2013; Ayana et al., 2016). Besides cultural traits, for example cattle-raiding (Witsenburg & Adano, 2009; Ember et al., 2012, 2014), other factors might make districts with substantial levels of pastoralism more susceptible to violence[13] – notably central government neglect, leading to higher poverty levels, malnutrition rates, and lower living standards in general (Stockton, 2012), creating circumstances where people might resort to violence for social advances (Greiner, 2013).

To account for the effect of pastoralism on violence, a binary indicator is included in the model, taking value 1 if a district's area overlaps for at least 25% with the pastoralist livelihood zone as defined by the FEWS Net data. The estimate shows an associated increase of 1.4 in the log count of the outcome variable for these districts, corresponding to about four events (50% UI: [3.2; 7.3]). Climate change could negatively affect households' abilities to cope with adverse changes such as increased drought frequency and severity (Berhe et al., 2017; Brown et al., 2017). Interacting the dummy variable with the precipitation variable shows that the effect of a change in precipitation on conflict risk is not different for districts with substantial levels of pastoralism (column 6).[14] This is possibly an indication that violence between groups takes place in a social context, rather than being motivated exclusively by climatic factors (Hagmann & Mulugeta, 2008; Ide et al., 2014; Linke et al., 2015).

Seter, Theisen & Schilling (2018) also highlighted the role of national-level processes. For instance in Kenya, conflict could be attributed to the devolution of power where different ethnic groups are pitted against each other to gain territorial control to guarantee national assembly representation (Greiner, 2013). Including a country indicator shows that Kenyan districts have higher conflict levels on average ($\delta = 0.6$; $Pr(\delta > 0) = 0.87$); conclusions concerning the effect of precipitation remain unaltered. Similarly, including an indicator for ethnic groups excluded from political power (Wucherpfennig et al., 2011) indicates that districts with excluded groups have higher conflict levels ($Pr(\delta > 0) = 0.92$), while again not changing the main conclusions. Finally, the income effect of precipitation might lower opportunity costs and tempt people to join ongoing insurgencies against the central government (Collier & Hoeffler, 1998). The region is host to a number of other types of conflict (see Figure A3 in the Online appendix). While communal conflict is the most common type of conflict in Kenya, Ethiopia particularly suffers from a number of local insurgencies by ethnic groups striving for self-determination such as in the Afar, Oromiya and Ogaden regions. Indeed,

[12] Population density data are taken from Global Rural-Urban Mapping Project, using 2000 estimate. Gridded data are aggregated to district level and divided by area to get the population density measure in people per square kilometers.

[13] Pinker (2012) provides a discussion on the cultural ramifications of the link between pastoralism and violence, drawing on Nisbett & Cohen (1996). Traditionally pastoralists tend to be more violent, as opposed to sedentary farmers, because their main asset, livestock, is more easily appropriated.

[14] These estimates are robust to changing the threshold of the district's area covered to 50% or 80%.

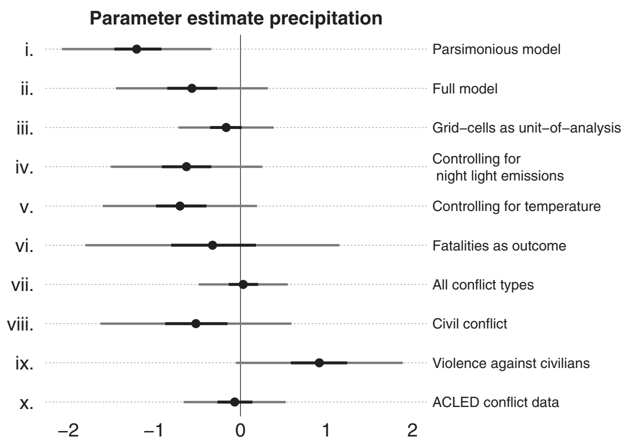


Figure 5. Estimated posterior distribution for precipitation variable showing the mean (point) and the 50% (black line) and 95% (grey line) uncertainty interval

Some results from Table I are included: column 2 (i), column 3 (ii), and column 7 (vi). Night light emission data come from the National Oceanic and Atmospheric Administration as used by Henderson, Storeygard & Weil (2012). In this case the change is taken between 1992/93 and 1997/98. Temperature data come from Earth System Research Laboratory; the change in average anomaly is used.

changing the outcome variable to include only civil-war related events (Figure 5(viii)) shows a negative link with the precipitation shift ($Pr(\delta < 0) = 0.83$), associating the decline with increased insurgency activity.

To deal with uncertainty resulting from using differences to measure climate change, the model is re-estimated including a variable giving the probability that district level precipitation has declines since 1998 (Table I, column 4). For this purpose the Bayesian estimation supersedes the t-test (BEST) is used (Kruschke, 2012).[15] Beforehand one would expect that districts with higher estimated probabilities of a precipitation decline are associated with higher conflict levels. The estimated effect corroborates this with the 50% UI ranging from 0.5 to 20.0 and $Pr(\delta > 0) = 0.86$.

Battle-related fatalities are used as outcome variable (Table I columns 7 and 8) to account for conflict intensity rather than quantity. Precipitation is a weak explanatory variable given the wide uncertainty intervals, reflecting results in Seter, Theisen & Schilling (2018). To examine the sensitivity of the results to different identifying assumptions, other model specifications are considered (Figure 5). The main results still stand when controlling for temperature or local economic activity (using night-light emissions as proxy). Uncertainty increases using a different conflict dataset that includes events with lower-intensity levels ($Pr(\delta < 0) = 0.59$), suggesting a weaker link with more incidental forms of violence.[16] The results could be driven by the chosen level of aggregation, leading to an ecological fallacy. Therefore grid-cells are used as an alternative unit-of-analysis, as they have the advantage of covering a fixed area (Buhaug & Rød, 2006). Using 0.5 grid-cells results in a reduction of 18 points compared to the district-level estimate but still indicates a likely negative correlation ($Pr(\delta < 0) = 0.73$). One surprise result is the strong positive correlation between precipitation and violence against civilians ($Pr(\delta > 0) = 0.97$). Even after consulting the literature, no explanation for this result is available.

### *Cross-validation*

Fitting a regression model, there is a risk of only modelling the data's idiosyncrasies. Therefore for further scrutiny and to test whether the results generalize, the model is used to predict the outcome for out-of-sample data using LOO. The preferred model (Table I, column 3) is re-estimated, fitting data from $N - j$ districts and predicting the outcome for left-out district $j$: this process is repeated for all 155 districts.

Figure 6 presents a marginal calibration diagram (Bagozzi, 2015), illustrating the accuracy of the model at aggregate level comparing the observed conflict event numbers with the observed frequency. The negative binomial model holds its ground, accounting for over-dispersion in the data as the number of zeros is only slightly underestimated (while the frequency of one event is overestimated). The other frequencies tend to be reasonably close to the observed levels, a notable outlier being the district with 56 conflict events.

Considering point predictions, Figure 7 plots the predicted values against (a) the observed precipitation change or (b) the estimated probability that precipitation decreased. Panel (a) shows that (i) districts with large decreases are matched with higher predicted values and (ii) most districts experiencing conflict also experienced precipitation declines.[17] Results are similar when using

[15] The BEST is used to estimate the probability that the precipitation levels for 1999–2014 are lower compared to 1981–98. The results are summarized in Figure A2 in the Online appendix.

[16] As an aside, the possible urban bias in these data (Eck, 2012) cannot be ruled out.

[17] A 0.3-standard deviation decrease on average compared to 0.2 standard deviations for districts without reported incidents of communal conflict.

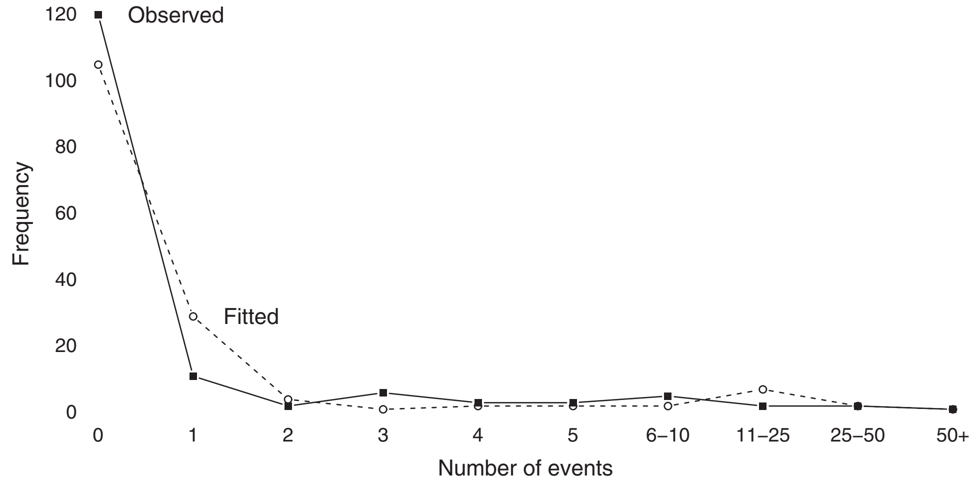


Figure 6. Marginal calibration diagram plotting the observed frequency of events versus the predicted frequency from a leave-one-out cross-validation, where one district is left out at a time and the outcome predicted by the model

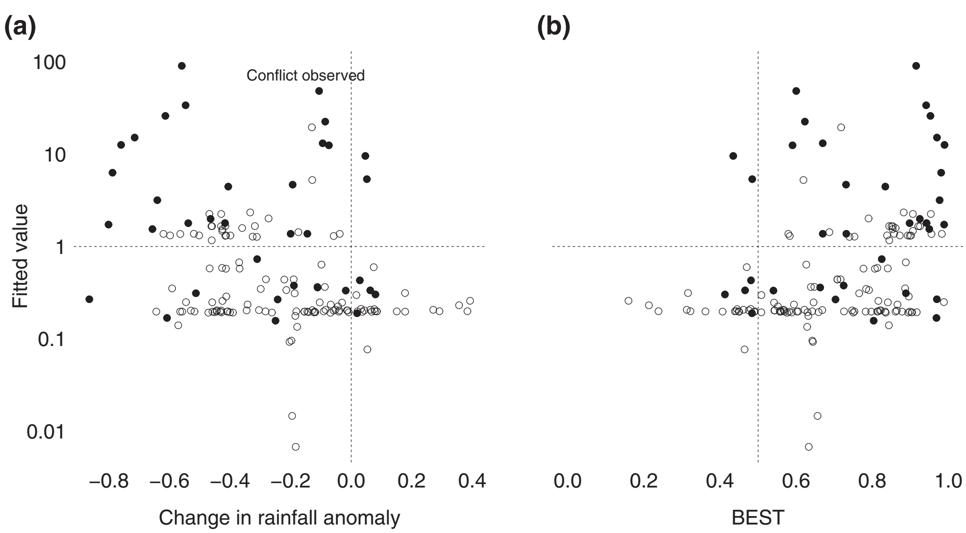


Figure 7. Scatterplots illustrating the relation between fitted values from leave-one-out cross-validation and the observed change in the average precipitation anomaly (a) and the estimate likelihood of change (b)

the estimated probability of a precipitation decrease (panel (b)). Note though that for a number of districts experiencing communal conflict there is more uncertainty whether there has been a precipitation decline as shown by the BEST estimate.[18]

Figure 8 panel (a) shows the absolute predictive error for each district, plotted against the observed conflict levels. The predictive accuracy is reasonable for districts without reported conflict events but the model seemingly has difficulties matching higher levels of communal conflict with higher fitted values. The model fails to accurately predict conflict quantity for individual districts, despite including information on conflict dynamics and other possible conflict determinants.[19] In fact the other variables do most of the heavy lifting as illustrated by Figure 8 panel (b). Comparing the LOO results from the preferred model with an identical model

[18] Possibly conflict risk is higher in relatively wet places (Theisen, 2012; Detges, 2014). A model specification including the spatial lag of $\Delta R_j$, to account for possible conflict displacement, did not show a strong effect: $Pr(\beta < 0) = 0.34$.

[19] Using grid-cells as unit-of-analysis presents no improvement (Figure A4 in the Online appendix).

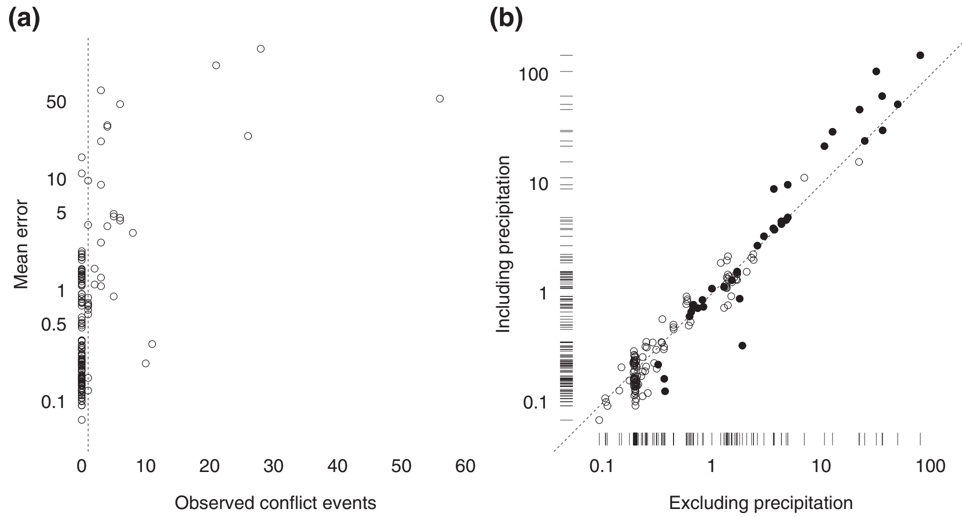


Figure 8. Forecast error per district, from leave-one-out cross-validation, compared to observed levels of communal violence (a) and comparing fully specified model (Table I, column 3) versus model omitting variable accounting for precipitation shift (b)

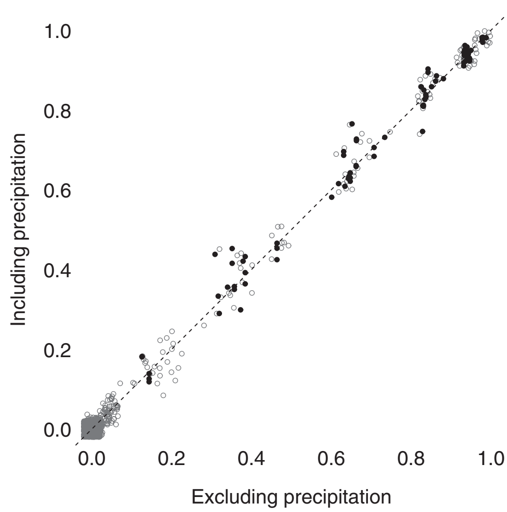


Figure 9. Brier score logit model predictions, exploiting time-series variation in the data ($N = 2,480$)

Random jitter applied to points to improve visibility.

omitting the precipitation variable does not lead to an increase in predictive error, illustrated by the clustering of data points around the 45-degree line. These result are not due to reliance on exclusively using cross-sectional variation. Relaxing assumptions and exploiting time-series variation fitting a logit model produces similar results, as illustrated in Figure 9.[20]

## Conclusions

There has been a surge in research on the climate–conflict nexus in recent years, amid growing concerns about possible negative societal effects of climate change. One limitation of research in this field is that most studies conflate climate variability with climate change (Buhaug, 2015) by relying on short-term weather variation to make inferences concerning the possible effects of global warming on conflict risk. This study aimed to address this issue using a quasi-natural experiment: a decline of the long rains season precipitation levels in the Horn of Africa following the 1998 El Niño. Focusing on communal conflict in Ethiopia and Kenya, the regression results show a negative correlation, linking districts that experienced historically lower precipitation levels with more reported conflict events. Results are robust to a number of changes in the identifying assumptions. Interpreting these results it is pivotal to see how well they generalize, specifically whether the model has any predictive power, not only to weed out bad theories (Ward, 2016) but also in terms of possible practical applications that can be useful to arrive at better informed policies (Ward, Greenhill & Bakke, 2010; Chadefaux, 2017; Blair, Blattman & Hartman, 2017). Cross-validating the model shows that its predictive performance is relatively mediocre in terms of matching the conflict levels for individual districts. Although on aggregate the model does reasonably well, accounting for overdispersion in

[20] The logit model is fitted following the specification in Table I column 3 using data covering 1999–2014. The 15-year moving average of the precipitation anomaly is used to identify the effect of climate change on communal conflict. A two-standard deviation increase in precipitation corresponds to a 10% decrease in conflict risk; the estimated effect is negative with probability 0.91.

the outcome variable, at the unit-of-analysis level the predictive errors are relatively large. Therefore, echoing Detges (2016), the correlation between precipitation and conflict should not be overstated. While climate variability might influence certain conflict dynamics (Nordkvelle, Rustad & Salmivalli, 2017), this study suggests that the effect of climate change so far has been moderate. To what extent the impact of the shift has been moderated by local institutions (e.g. Adano et al., 2012; Linke et al., 2015) remains open to speculation. In addition there are other factors that can help explain communal conflict, such as devolution in the case of Kenya (Greiner, 2013) or expansion of the state towards peripheral areas in Ethiopia (Hagmann & Mulugeta, 2008). In the econometric framework these processes have been accounted for by including a country indicator, which basically means that it is controlled away as a statistical nuisance. This interplay between national and local factors is something that deserves further attention in future empirical research.

Finally, an important caveat of this study is that the analysis is based on a reduced-form model. As such, it captures correlations but provides few insights into specific mechanisms, leaving some ambiguity. Data constraints prevented closer examination of particular causal channels such as local prices (Maystadt & Ecker, 2014) or trade between ethnic groups (Olsson, 2016), which also hinders making specific policy recommendations. This is work left for the future. The results should therefore be considered complementary to existing small-N and anthropological studies, which focus more on causal mechanisms and specific contexts but might lack external validity.

## Replication data

The replication data, code, and Online appendix for this article can be found at http://www.prio.org/jpr/datasets. All analyses were conducted using R.

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