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Rainfall Inequality, Political Power, and Ethnic Conflict in Africa*

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Abstract

Does higher resource inequality between ethnic groups lead to ethnic conflict? In this paper, we empirically investigate this question by constructing a new measure of inequality using rainfall on ethnic homelands during the plant-growing season. Our dataset covers the period 1982-2001 and includes 214 ethnicities, located across 42 African countries. The analysis at the country level shows that one standard-deviation increase in rainfall-based inequality between ethnic groups increases the risk of ethnic conflict by 16 percentage points (or 0.43 standard deviations). This relationship depends on the power relations between the ethnic groups. More specifically, the analysis at the ethnicity level shows that ethnic groups are more likely to engage in civil conflicts whenever they receive less rain than the leading group. This effect does not hold for ethnic groups that share some political power with the leading group and is strongest for groups that have recently lost power. Our findings are consistent with an increase in resource inequality leading to more ethnic conflicts by exacerbating grievances in groups with no political power.

JEL classification: D63, D74, E01

Keywords: Conflict, Ethnic Inequality, Rainfall, Africa, Ethnic Power Relations

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1. Introduction

Since World War II, civil conflicts have caused three times as many deaths as interstate conflicts (Fearon and Laitin, 2003). One out of three civil conflicts took place in Africa and the majority of them were fought along ethnic lines (Wimmer et al., 2009).[1] But what causes civil conflicts? For decades academics and policy makers have tried to identify common determinants. The vast empirical literature on civil conflict broadly agrees on the importance of a few factors, such as income per capita and institutional quality, but is still very much divided on most of the others (Hegre and Sambanis, 2006). In particular, the role played by economic inequality across ethnic groups has been strongly debated in this literature. The controversy has been fueled by the difficulties in empirically investigating the relationship between inequality and civil conflicts, due to the lack of disaggregated income data and to identification challenges.

In this paper, we rely on rainfall data to construct a new measure of inequality between ethnic groups and investigate the relationship between inequality and ethnic civil conflicts across Africa. More specifically, we calculate a Gini-type measure of *Between-Group Rainfall Inequality* (BGRI) using the amount of rainfall each ethnic homeland receives. Our strategy relies on rainfall affecting agricultural production and water supply, on which the livelihood of most people across Africa depended during our sample period.

Our reduced-form results indicate a large and significant effect of BGRI on ethnic conflict prevalence at the country level. We find that a one standard-deviation increase in BGRI increases ethnic conflict prevalence by 16 percentage points (or 0.43 standard-deviations). This implies almost doubling the risk of ethnic conflict, compared to the

[1] *Civil conflicts*, as defined by the Peace Research Institute Oslo (PRIO), are armed conflicts between the government of a state and one or more internal opposition group(s) that cause at least 25 battle-related deaths within a year. *Ethnic civil conflicts*, as defined by the Ethnic Armed Conflict (EAC) database, are civil conflicts in which armed groups: i) explicitly pursue ethno-nationalist aims, motivations, and interests; and ii) recruit fighters and forge alliances on the basis of ethnic affiliation.

average prevalence in the sample (18%). In line with our interpretation, the effect disappears when we consider non-ethnic conflicts. Moreover, consistent with the proposed link with agricultural income, the effect entirely stems from rainfall during the plant-growing season.

Two additional tests support our approach. First, at the *country* level, our measure of rainfall during the growing season is significantly associated with agricultural production; while rainfall outside the growing season is not. Second, for a sub-sample of years, we show that, at the disaggregated *ethnicity* level, our measures of rainfall and rainfall-based inequality are positively related to economic activity and economic inequality, as proxied by nightlight density per capita – to the best of our knowledge, the only proxy that is available in a disaggregated form and on a yearly basis.

The results pass a large set of placebo tests and robustness checks. Most importantly, we cannot replicate our findings using either administrative regions or a hundred sets of randomly-drawn placebo group boundaries to calculate BGRI. Second, we rule out that the result is simply driven by settings in which ethnic groups are highly polarized. Third, we address a number of potential threats to our identification strategy by including a rich battery of controls. Among these are rainfall along the main roads, malaria incidence, and previous conflict history. Finally, our BGRI measure is a much stronger predictor of ethnic conflict prevalence than the country-wide measure of rainfall growth used in the seminal paper on rainfall and civil conflicts by Miguel et al. (2004).

To better understand the mechanisms, in the second part of the paper we investigate how our results depend on the political power distribution across ethnic groups. We show that the relationship between inequality and conflict is driven by changes in the distribution of rainfall between the politically most powerful ethnic group and the other groups.

To zoom in even further, we complement the analysis at the country level with an analysis at the (country-)ethnicity level. Our results show that non-leading ethnic groups are more likely to be involved in an ethnic civil conflict whenever they receive *less* rainfall than the leading group. We do not find evidence for an increase in conflict prevalence when they receive *more* rainfall. Furthermore, the effect does not hold for ethnic groups that still share some political power with the leading group and is strongest for groups that have recently lost power.

Although we do not have detailed information on which side started the conflict and on the motivations of the different groups, our findings are consistent with inequality leading to higher conflict prevalence by exacerbating grievances in ethnic groups with no access to political power.

We wish to point out that our measure of inequality captures short-term changes in the distribution of (agricultural) resources and is therefore ill-suited to test hypotheses related to persistent wealth or income gaps within the society. However, differences in yearly rainfall resources are likely to reflect welfare differences, especially across the African continent, where a large fraction of people directly depend on agriculture for their livelihoods. Besides, anecdotal evidence from Sudan, Ethiopia, and Uganda confirms that climatic factors affecting the distribution of agricultural resources across different ethnic groups have significantly contributed to the intensification of armed conflicts (UNEP, 2007; USAID, 2013).[2] We also acknowledge that rainfall might affect conflict through channels other than income or food production. While providing a number of checks that suggest that our reduced-form effect works through income, we cannot fully rule out the contribution of additional channels.

Notwithstanding these limitations, our analysis delivers a number of relevant implications. First, the results represent a clear warning signal in light of the ongoing climate change. Long-term climate change is associated with higher short-term weather variability and more extreme weather conditions (Semenov and Barrow, 1997; IPCC, 2014).

[2] Using micro-level data, Ralston (2015) shows that ethnic tribes in the Karamoja region of Uganda that suffer from poor rainfall are more likely to initiate attacks against other groups, whereas groups that benefit from good rainfalls are more likely to be targets of the attacks.

These are likely to lead to larger variations in the distribution of rainfall, increasing the risk of ethnic conflicts. In terms of policy advice, our results imply that interventions that make the agricultural system less climatic-dependent (e.g. through extended irrigation systems), as well as national policies providing compensation for groups affected by relatively worse weather, can help reducing the risk of ethnic conflicts. Moreover, our analysis suggests that inclusive political institutions can play a key role in settling ethnic tensions.

Overall, our work contributes to three different strands in the conflict literature: the literature on economic inequality, on climate, and on ethnic politics.

First, this paper speaks to the long-standing literature on the relationship between inequality and armed conflicts.[3] Empirical studies have typically struggled to provide evidence of this link, mostly due to severe data and methodological constraints. Recent studies that focus on economic inequality between groups mostly rely on data from surveys, nightlight density satellite images, or digital maps of economic activity (e.g. Østby, 2008; Huber and Mayoral, 2014; Kuhn and Weidmann, 2013; Cederman et al., 2011), which are unlikely to provide exogenous variation and often are only available for a few years.[4] In this paper we tackle the endogeneity issue and circumvent the lack of disaggregated income data, by constructing a new inequality measure based on high-frequency rainfall data.[5]

In doing so, we borrow insights from a fast growing literature on climate and con-

[3]Early examples include Russett (1964), Parvin (1973), and Nagel (1974).

[4]There are multiple issues related to the use of survey data. First, income measures captured through surveys tend to be noisy and unreliable (Beegle et al., 2012; de Nicola and Giné, 2014). Second, survey data are not annually available (two-fifths of all countries fail to conduct a household survey every five years (Chandy, 2013)), and aggregation and/or extrapolations are typically applied, adding to the measurement error. Finally, areas and periods where conflicts are more likely are also typically more difficult to survey and, are therefore likely to be under-represented in the data, further biasing the analysis. Concerning nightlight density and economic activity data, on top of potential endogeneity issues, the datasets are only available for a very limited number of years.

[5]To the best of our knowledge, Morelli and Rohner (2015) is the only other study on inequality and conflicts that relies on a time-varying ethnic inequality measure (based on oil and gas fields). However, in this case variation in the inequality measure stems from the discovery of new fields. Although the authors discuss why this does not pose a major threat to the analysis, we believe that using rainfall data addresses more convincingly any endogeneity concern.

flict, which followed the seminal paper by Miguel et al. (2004). Across a large number of settings, this literature has found that locations experiencing worsened climatic conditions tend to experience also higher risk of conflict (for a review, see Burke et al., 2015).[6] But while this literature has focused on the *local* effect of rainfall (or temperature) – and, in few cases, on how the effect propagates (Harari and La Ferrara, 2014) – in our study we look at the impact of the *distribution* of rainfall, thereby introducing a new and so far neglected dimension in the analysis.

Finally, a growing body of studies investigates the role of power relations across ethnic groups, finding that grievances in groups that are excluded from power are a strong force behind many armed conflicts (for a review, see Cederman et al., 2013). Our analysis confirms these results and, in addition, shows that changes in the distribution of resources can further exacerbate these grievances, leading to higher conflict prevalence. Our results also provide novel evidence in support of the claim that political representation across Africa has been extensively used as an instrument to manage ethnic relations (Francois et al., 2015), as we find that ethnic groups that share some power with the leading group are less responsive to exogenous changes in resource distribution that penalize them.

The remainder of the paper is organized as follows. Section 2 briefly introduces the conceptual framework for the analysis. Section 3 details the data sources that are combined to generate the dataset. Section 4 discusses the empirical analysis at the country level. It starts by defining our measure of inequality and empirical framework and then illustrate the various results, discussing in detail their robustness. Section 5 follows a similar structure, but focuses on the analysis at the ethnicity level. Finally, Section 6 concludes.

[6]For completeness, it should be mentioned that agreement over the link between climate and conflicts is not universal. See for instance Buhaug et al. (2014) for a summary of the opposite view.

2. Conceptual framework

The link between economic inequality and armed conflicts goes back to the theory of *relative deprivation* (Gurr, 1970): as individuals tend to compare themselves to others, inequality is likely to lead to grievances and frustrated expectations in those lagging behind, ultimately increasing the risk of violence and conflicts. While intuitively appealing, early empirical studies that relied on individual-level inequality measures, mostly found no support for this theory (Collier and Hoeffler, 2004; Fearon and Laitin, 2003; Hegre et al., 2003). One possible explanation is that, when it comes to armed conflicts, what really matters is inequality along the lines of certain groups, rather than between individuals (Montalvo and Reynal-Querol, 2003; Esteban and Ray, 2005). Ethnicity is an especially relevant dimension, as it typically founds itself on a combination of key factors such as language, race, and religion (Horowitz, 1985; Østby, 2008; Esteban and Ray, 2008). Inequality between ethnic groups might thus facilitate mobilization for conflict by enhancing grievances between the different groups and increasing cohesion within the same group (Østby, 2008).

Ethnic violence is often interlinked with ethnic politics. Indeed, ethnic conflicts are often depicted as the violent manifestation of long-standing tensions between ethnic groups, typically founded on competition over access to state power in countries with weak political institutions. Control over state power has been found to guarantee a more favorable allocation of state resources towards the members of the leading groups (Hodler and Raschky, 2014; Burgess et al., 2015), and grievances caused by exclusion from power have been shown to be a key driver of armed violence (Cederman et al., 2013). Within this context, an exogenous variation in the distribution of resources that favors the group in power might exacerbate existing grievances, leading to an higher the risk of armed violence.

Another interpretation, consistent with a less favorable distribution of resources for the excluded groups leading to higher risk of ethnic conflict, is based on an opportunity-cost evaluation: as a consequence of the increased gap with respect to the leading group, the excluded group has relatively less to lose and more to gain from the conflict. While the set of results that we will discuss appears consistent with grievances playing a major role, the data at our disposal will not allow us to fully rule out the opportunity-cost story. Overall, it seems likely that grievances and opportunity-cost considerations reinforce each other, as groups that are politically penalized might find it easier to mobilize group members for conflict, both because of increased grievances and because conflict becomes more convenient.

3. Data

We combine information from several different sources to construct our dataset, which comprises 42 African countries.[7] Based on data availability (see below), our main analysis covers 20 years, from 1982 to 2001. Table C.1 reports the full list of countries included in the study. Summary statistics for the different variables are reported in Table 1. In the interest of space, in this section we only provide an essential description of each variable and source, while more details can be found in Appendix A.

3.1. Key variables

Conflicts To construct the dependent variable we rely on the Ethnic Armed Conflict (EAC) dataset provided by Wimmer et al. (2009). The dataset builds on the PRIO/Uppsala armed conflict database (Gleditsch et al., 2002), which, among other things, records all civil conflicts that took place across the globe on a yearly basis, since 1946. For each civil

[7]We exclude islands and small territories, because most of the data sources used in the analysis do not cover them. We moreover exclude Madagascar and Lesotho, because these countries host the homeland of one single ethnic group and therefore, by definition, ethnic inequality cannot be computed and ethnically motivated conflicts cannot take place. Finally, we exclude Eritrea and Namibia because the two countries only reached independence during the period under consideration. Results remain in any case unaffected by the inclusion of these countries (available on request).

conflict, the EAC dataset identifies whether: 1) the armed organizations involved in the conflict explicitly pursued ethno-nationalist aims, motivations, and interests, and 2) they recruited fighters and forged alliances on the basis of ethnic affiliations. We generate an indicator variable for the presence of an ethnic conflict in a country in a given year, whenever the two conditions are jointly fulfilled.[8] Table C.1 details for each country the number of years of ethnic and non-ethnic conflicts over the period under consideration, while Figure B.1 visually illustrates of their distribution across the sample.

Ethnicity For the first part of the analysis, ethnic group information stems from the Geo-Referencing of Ethnic Group (GREG) map provided by Weidman et al. (2010). The map was created by digitizing and merging the 57 maps that constitute the *Soviet Atlas Narodov Mira* (1964), which describe the spatial distribution of ethnic groups around the world as of the early 1960s. The GREG map has already been extensively used in the literature (Easterly and Levine, 1997; Esteban et al., 2014; Alesina et al., 2016). Our main dataset includes 214 different ethnicities, with an average of 11 (median is 10) different ethnicities per country (see Table C.1 for details).

While using historic ethnic homelands addresses endogeneity concerns, one might wonder how the ethnic distribution changed over time and how well the *Soviet Atlas* map reflect more recent ethnic diversity in Africa. There are a number of studies suggesting that migration patterns are unlikely to have significantly reshaped the overall location of the main ethnic groups, even after major conflict episodes, such as those in Sierra Leone or Rwanda (Glennerster et al., 2013; UN, 1996). Moreover, if anything, a low accuracy of the data should add noise to our estimations, biasing our results downwards. Nevertheless, in the second part of the analysis we directly address this issue, using an alternative *dynamic* set of digitized maps, provided by Wucherpfennig et al. (2011). The

[8]This is the same criterion used by the Wimmer and coauthors to define ethnic conflicts. Within our sample, the two conditions are in any case always jointly satisfied, with the only exception of Ethiopia between 1996 and 1999, when only condition 1 is satisfied. Considering this conflict as ethnic leaves our results unaffected (results available on request).

Geo-referencing Ethnic Power Relations (GeoEPR) maps trace the location of the ethnic groups included in the EPR dataset (described below) over time. As such, the GeoEPR maps has smaller coverage than the GREG map. Moreover, differently from the GREG map, the GeoEPR maps are dynamic and portray the actual occurrence of ethnic group members in a specific region, rather than focusing on ethnic *homelands*. The classification and localization of ethnic groups is based on expert panels and is somewhat different from the one adopted in the GREG map.[9]

Ethnic Power Relations Information on the power relations across ethnic groups is taken from the Ethnic Power Relations (EPR) dataset provided by Girardin et al. (2015). The dataset contains disaggregated information on all politically relevant ethnic groups within a country, including their estimated size and their level of access to state executive power.[10] The EPR dataset assign each politically relevant ethnic group to one of three main categories of access to executive power, each one composed of two sub-categories. First, an ethnic group can rule alone, as *Monopolist* or *Dominant* group, depending on whether there is space for limited inclusion of other parties in the executive body or not. Second, a group can formally or informally share executive power with other ethnic groups, being either a *Senior Partner* or *Junior Partner* in the arrangement. Finally, a group can be excluded from power, and thus be *Powerless* or *Discriminated*, depending on whether there is explicit active discrimination against it or not. The dataset is dynamic and whenever political changes occur in the same year as a conflict, the coding purposely reflects the power relations *before* the outbreak of the violence.

Importantly, the EPR dataset can also be linked to the Uppsala Conflict Data Program (UCDP) Actor Dataset (2014), which records all actors that were involved in a civil conflict. The matching allows identifying which ethnic groups were associated with the

[9] Table C.2 shows the list for countries and the corresponding number of ethnic groups included in the dataset based on the GeoEPR maps.

[10] An ethnic group is considered politically relevant if either at least one significant political actor claims to represent the interests of that group in the national political arena or if group members are systematically and intentionally discriminated against in the domain of public politics (Girardin et al., 2015).

different rebel actors fighting the central state in an ethnic civl conflict. Hence, differently from the analysis based on the *Soviet Atlas*, whenever using the EPR dataset we can identify exactly the ethnic groups involved in the violence.[11]

Rainfall We use the ERA-40 dataset, which contains rainfall data provided by the European Centre for Medium-Term Weather Forecasting (ECMWF). The dataset provides reanalysis of weather data, obtained through a climatic model that harmonizes information from a variety of primary sources (for more details, see Kållberg et al., 2004). This appears to be one of the best available sources for African weather data, especially given the sparse location of rainfall station throughout the continent. The dataset provides rainfall information at a six-hour frequency from 1958 until 2001 and at a 1.25 degree resolution (corresponding to about 140 square kilometers at the equator). On average, each country in our sample is covered by 52 rainfall grid-cells (median is 43). While some noise in rainfall data is unavoidable, precision is expected to be significantly better once global satellite data became available, in the late seventies – right before the beginning of our study period. Moreover, the fact that data are provided in spatially aggregated format (at 1.25 degree resolution), and that we temporally aggregate them to construct our measures of interest, helps attenuating the noise in the rough data.

In constructing our measure of rainfall during the growing season, we follow a similar approach as Kudamatsu et al. (2014). We rely on the Normalized Difference Vegetation Index (NDVI) dataset provided by Tucker et al. (2005), which contains the mapping of bi-weekly measures of plant growth, available since January 1982 with a high resolution of 8×8 km. We then use a software to remove the noise from the NDVI data and extract seasonality information, allowing us to determine the yearly growing season within each 8×8 km NDVI pixel (see Appendix A for more details). Then, we aggregate that fine-gridded measure at the 1.25×1.25 degrees resolution to obtain the average plant-growing

[11] One caveat to keep in mind is that ethnic groups ruling alone can never be recorded as involved in any ethnic conflict, according to this definition, because, because they can never fight the central state, which is under their sole control.

season within each rainfall grid-cell. Finally, we overlay the grids with the spatial ethnicity and administrative maps and compute the average rainfall during the growing season for each ethnic group and country. Figure 1 visually illustrate the way the different data sources are combined when considering the GREG map.[12]

One caveat to keep in mind with our approach is that we approximate potentially different crop-specific growing seasons with the vegetation growing season captured through the NDVI. This approach is likely to add some noise to our measure, which, if anything, should bias downwards our estimates. Given the importance of rainfall in our analysis, we will in any case validate our measure by showing that, at the country level, rainfall during the growing season strongly predicts agricultural production as recorded by FAO, while rainfall outside the growing season does not have any significant predictive power.[13]

3.2. Additional variables

In order to validate and test the robustness of our results, we construct a number of additional measures, combining additional data sources.

As mentioned above, we rely on FAO (2015) data to link our rainfall measure to *agricultural production*. More specifically, FAO records information on four key aggregates: cereals, crops, agriculture, and food. Estimates on production are based on information collected from governments as well as from national and international agencies and organizations.

In another validation check, we test whether rainfall and rainfall-based inequality map into *nightlight density* and *nightlight-based inequality*, respectively. Allegedly, nightlight density is not a perfect proxy for income and development, but it has been extensively

[12] Figure B.2 provides the corresponding image when the GeoEPR maps are considered instead.

[13] Kudamatsu et al. (2014) also show that rainfall during the growing season, estimated using the procedure detailed above, is significantly related to local crop prices in Sub-Saharan Africa, as measured by the USAID Famine Early Warning Systems Network (FEWS NET).

used as such in the recent economic literature, mostly due to the lack of better alternatives.[14] Data on nightlight density is provided by the National Geophysical Data Center (NGDC) on a yearly basis, starting from 1992. Data comes at a very high resolution, equal to approximately 0.86 square kilometers at the equator. [15]

In our robustness checks we also include measures of *temperature* during the growing season and *temperature-based inequality*. This is meant to limit the risk of omitted variable bias, in light of the typically high correlation across climatic variables. We rely on temperature data made available by the ECMWF with the same frequency (six hours) and resolution (1.25 $\times$ 1.25 degrees) as the rainfall data.

Especially in Sub-Saharan Africa, rainfall is expected to directly affect *malaria prevalence*, which might in turn affect the likelihood of a conflict, for instance by hampering the ability of individuals to fight. In order to control for this possibility, we follow again Kudamatsu et al. (2014) and construct a monthly indicator for malaria risk. The variable takes on the value of one whenever four different temperature- and rainfall-related conditions, determining the ability of malaria parasites and vector to survive and regenerate, are jointly satisfied (see Appendix A for more details). For each 1.25 $\times$ 1.25 degree gridcell we compute the share of months within a year in which the malaria-prevalence index is equal to one. Finally, we take the weighted average of this measure across all grids covering a country in order to obtain a country-specific measure of malaria prevalence.

We also construct a measure of *rainfall-induced transportation costs*, to control for the fact that rainfall can significantly increase transportation costs, especially in areas with poor infrastructure (dirt roads). We rely on the digitized map of the road system provided by the Global Roads Open Access Data Set (gROADS) and generate our variable of interest following Rogall (2015). We first create a small buffer (10 meters) around each road and

[14]See for instance Henderson et al. (2012); Chen and Nordhaus (2011); Hodler and Raschky (2014); Michalopoulos and Papaioannou (2013, 2014); Kuhn and Weidman (2013); Alesina et al. (2016).

[15]Following Alesina et al. (2016), we weight nightlight density by the population living in the area, using data from the Gridded Population of the World.

then compute the yearly amount of rainfall over each buffer.[16] Finally, we weight the road-specific rainfall measure by each road's relative length to obtain the country-specific average.[17]

4. Analysis by Country

4.1. Empirical Framework

In the first part of the analysis our unit of interest is a country-year observation. We start by relying on the GREG map to construct a measure of rainfall inequality between ethnic groups living in the same country. This measure represents our proxy for resource inequality and we are then interested in studying its impact on ethnic civil conflict prevalence.

More specifically, our measure of Between-Group Rainfall Inequality measure (BGRI) is inspired by the standard Gini coefficient and is calculated for each country and year as

$$BGRI = \frac{1}{2\bar{r}} \sum_{i=1}^{E} \sum_{j=1}^{E} n_i n_j \mid r_i - r_j \mid \tag{1}$$

where E indicates the number of ethnic groups whose homeland is located within the country, n_i is the relative size of ethnic group i[18], r_i is the amount of rain that fell over ethnic group i's homeland, and $\bar{r}$ is the average amount of rain that fell over the whole country during the year (to allow for cross country comparisons). [19]

[16] As the rainfall grid comes at a much lower resolution, the exact size of the buffer does not really matter. We chose 10 meters because the high number of roads in our dataset makes computation very slow, and larger buffers make it even slower.

[17] In the rich set of robustness checks that reported in Appendix, we also consider additional variables that have been found to affect conflict prevalence. Details of these additional measures and their sources can be found in Appendix A.

[18] In cases in which different ethnic groups' homelands overlap, we equally divide the overlapping area among the different groups, thus assuming they have equal size over that area.

[19] Figure B.3 illustrates for each country the average and standard-deviation in the BGRI measure – based on rainfall during the growing season – over the period 1982-2001.

The use of a rainfall-based inequality measure shelters our analysis from any potential reverse causality issue. However, it might raise concerns about what we are actually capturing with our measure. While our focus will be on the link between rainfall and (agricultural) resources, it might be the case that additional channels play a role in the link between rainfall inequality and ethnic conflict. We try to ease this concern in different ways. First, as anticipated above, in constructing our inequality measures we exploit the fact that rain is most "productive" when it falls during the growing seasons. Second, thanks to the yearly frequency of our data, in our empirical specification we control for a large set of fixed effects, significantly decreasing the risk of omitted variable bias. Finally, to cut off additional potential confounding effects, we run robustness checks explicitly controlling for a rich set of additional variables.

Main Specification Our main specification investigates the relationship between rainfall-based inequality and the prevalence of ethnic conflict at the country level. The corresponding empirical model is:

$$EthnicConflict_{c,t} = \lambda BGRI_{c,t} + \Psi \mathbf{X}_{c,t} + \tau_c + \phi_t + \kappa_c t + \eta_{c,t} \tag{2}$$

where the dependent variable is an indicator taking on the value of 1 if country c experienced ethnic conflict in year t, $BGRI$ is our rainfall-based inequality measure and $\mathbf{X}$ is a vector of controls that will be detailed below. Country fixed effects τ_c capture time-invariant characteristics, such as history or topography. Some studies for instance found that hilly terrains increase the likelihood of conflict (Buhaug and Rød, 2006; Miguel et al., 2004). Importantly, factors such as the colonial past, culture and institutions that do not change over time (or do so only over a longer time horizon than the one considered here) are also captured by this term. By including year fixed effects ϕ_t and country-specific linear time trends $\kappa_c t$ we further control for time-specific common shocks across the African continent (e.g. global economic shocks, or the signing of a new global agreement), as well as for country-specific trends and dimensions that change smoothly over time (e.g. years since independence). Finally, $\eta_{c,t}$ is the error term. We allow standard errors to be correlated over time for the same country and across countries for the same year.[20] The coefficient of interest is λ and a positive coefficient indicates that higher levels of inequality within the country lead to higher ethnic conflict prevalence.

With a binary dependent variable, the natural approach would be to estimate a logit (or probit) model. However, in our analysis we prefer using standard OLS estimation, fitting an unrestricted linear probability model, to make interpretation easier and avoid selection bias. A logit (or probit) model would indeed force us to exclude countries that never experienced any ethnic conflict, as in those cases the outcome would be perfectly predicted by the country effect. This fact and the easier interpretation of the OLS estimates makes them often preferred in the literature (Beck, 2015).

4.2. Main Results

Our main results are reported in Table 2. Regression 1, without any controls, shows a significant positive relationship between BGRI and ethnic conflict prevalence, with a point estimate of 0.338 (p-value=0.083). When we add the full set of country and year fixed effects, as well as country-specific linear time trends, the relationship strengthens both in terms of magnitude (0.706) and significance (p-value=0.038, regression 2). The estimated effect is large: considering the full sample, one standard-deviation increase in BGRI (equal to 0.23) leads to a 16 percentage point (or 0.43 standard-deviation) increase in ethnic conflict prevalence. This implies almost doubling the risk of ethnic conflict compared to the average prevalence in the sample (18%). Figure B.4 graphically illustrates the positive relationship between BGRI and ethnic conflict across the sample.

[20] As the theory underlying two-way clustering relies on asymptotics in the dimension containing the fewer clusters, we apply a finite sample adjustment, by scaling the variance-covariance matrix corresponding to the parameter estimates by $M/(M-1)$, where M is the number of years. The analysis is robust to alternative choices, such as clustering standard errors by country only (results available on request).

The effect of BGRI also shows some time persistence. The coefficient on lagged inequality is relatively large up to two years back in time, although it is only significant at conventional levels for the first lag (regression 3).[21] Importantly, the effects are not simply driven by local rainfall levels or by ethnic-specific climatic conditions. Regressions 4 and 5 show indeed the that positive link between inequality and conflict is confirmed both when we include a control for the amount of rainfall in the country and when we re-compute the inequality measure described in equation (1) replacing the level of rainfall r_i with the deviation from the group-specific average rainfall over the study period ($\tilde{r}_i$), expressed in standard-deviation units, i.e. $(r_i - \tilde{r}_i)/SD_{r_i}$.[22]

4.2.1. Validation Checks

To substantiate our argument that rainfall-based inequality is related to economic inequality, we perform two checks. First, we test whether more rainfall during the growing season is associated with more agricultural production. Second, we check how rainfall and rainfall inequality relate to nightlight density and nightlight inequality, which are the best proxies at our disposal, given the lack of systematic disaggregated income data.

We start by considering the four key agricultural aggregates recorded by FAO: cereals, crops, agriculture, and food. Results, reported in Table 3, confirm our conjecture: more rainfall during the growing season is significantly associated with higher agricultural output in all four cases, irrespectively of the inclusion of rainfall outside the growing season in the model (regressions 1 to 8). Furthermore, and again consistent with our conjecture, our results show that rainfall outside the growing season does not have any effect

[21] In order to preserve the number of observations when including the lags, we assume the growing season for the years 1980 and 1981 (for which we do not have NDVI data) to be the same as the average growing season over the period 1982-2001. Results are confirmed – although coefficients are slightly less precisely estimated – when those years are instead excluded from the analysis (see regressions 1 and 2 in Table C.4, Appendix C).

[22] As measures are expressed in standard-deviation units, in this case we do *not* divide the weighted sum by the average rainfall in the country $\bar{r}$. Table C.3, in Appendix C, reports the correlation matrix for all the country-wide inequality variables used in the empirical analysis.

on agricultural production (regressions 2, 4, 6, and 8). In terms of magnitude, the estimated effects are substantial. Looking for instance at overall agricultural production, the coefficient of 5.485 (p-value=0.012) in regression 5 indicates that one standard-deviation increase in rainfall during the growing season implies a 0.41 standard-deviation increase in the production index – corresponding to an 11% increase with respect to the average production.

We then move to investigate whether our rainfall measure is associated with economic activity at the sub-national level. As mentioned, in the absence of disaggregated income data, we rely on nightlight density. This analysis should be taken with a grain of salt, as nightlight density is certainly not a perfect measure of income, especially for rural areas, and it is moreover only available since 1992. One could however expect that as agricultural production and income increase, also local economic activity increases, for instance through more intense trading activities in local markets, leading to relatively more nightlight consumption. Keeping in mind the limitations of this measure, Table 4 reports the results of our analysis. Regression 1 shows that at the (country-)ethnicity level more rainfall during the growing season is associated with higher nightlight density per capita, although the relationship is only significant at the 10% level (0.045, p-value=0.084). When we include the measure of rainfall outside the growing season, we find our previous results broadly confirmed: the coefficient on rainfall outside the growing season is far from significance and, if anything, negative, while the one on rainfall during the growing season remains stable (0.049), although now the coefficient is less precisely estimated and falls just above the threshold for being significant at 10% level (p-value=0.103). Finally, we check whether our BGRI measure is positively associated with a measure of Between-Group Nightlight Inequality (BGNI).[23] Consistent with our previous findings, the relationship is entirely driven by rainfall during the growing season (regressions 3 and 4), while the coefficient on BGRI outside of the growing season is small (0.016) and

[23] BGNI is constructed in the same way as BGRI, using nightlight density instead of rainfall.

not statistically significant (p-value=0.474). Finally, also in this case there seems to be some persistence in the relationship, as the lagged measure of BGRI has a positive impact on current BGNI, although the estimated coefficient does not reach statistical significance (regression 5).

4.2.2. Falsification Tests

We next perform a number of falsification tests, reported in Table 5. Reassuringly, also in this case inequality based on rainfall outside of the growing season has no effect on ethnic conflict prevalence, neither when it is included in the same regression as inequality based on rainfall during the growing season (regression 1), nor when it is considered alone (regression 2).

While Table 2 showed some persistence in the effect of rainfall inequality, regressions 3 and 4 reassuringly show that inequality in year $t+1$ does not have any significant effect on ethnic conflict prevalence in year t.

An additional concern is that the ethnic homelands map might simply be picking up administrative unit boundaries, potentially affecting the interpretation of our results. To ease this concern we re-compute the BGRI measure using the 1990 level 1 administrative borders (typically corresponding to regions or districts) provided by GAUL. A horse-race with our original ethnicity-based measure is clearly lost (regression 5). Furthermore, even when considered alone, the new measure does not have any significant effect on ethnic conflict (regression 6).

To further rule out that something other than ethnic inequality might be driving the results, we randomly redraw the African ethnic boundaries a hundred times (fixing the original area distribution) and recalculate our BGRI measure with those placebo boundaries.[24] We then run 100 horse races between our original BGRI measure and the placebo measures. The distribution of the estimated coefficients is reported in Figure B.5, which

[24] The exact procedure to calculate our placebo boundaries is given in Appendix.

shows that the estimated coefficient of the placebo measure is centered around 0 and is never larger than the estimate of the corresponding true-ethnic-boundary measure.

Finally, since our measure focuses on ethnic inequality, it should not be able to predict non-ethnic conflict. In line with this conjecture, regression 5 shows that when we replace the dependent variable with an indicator for civil conflicts that are *not* classified as ethnic by the EAC dataset, the estimate becomes statistically insignificant and, if anything, negative.

4.2.3. Robustness checks

We next run a set of robustness checks. Results are reported in Table 6. First, one might be worried that our results are driven by settings in which ethnic groups are highly polarized.[25] To test for this, we construct two measures. First, we compute a measure of ethnic polarization, based on Montalvo and Reynal-Querol (2005).[26] Second, we construct a new measure of rainfall inequality that does not take ethnic boundaries into account, but simply compares rainfall across the gridcells included within country borders.[27] We then interact these two measures to test whether a more unequal distribution of rainfall across a country matters more in highly polarized settings. The estimates reported in regression 3 show that the interaction term is not statistically significant, while the effect of BGRI

[25]By definition, our inequality measure picks up differences in rainfall across the homelands of the different ethnic groups. The way ethnic groups are distributed across the country (e.g. whether groups are more or less spread out) therefore matters for our measure. Although this does not represent a threat to our analysis *per se*, given that our identification stems from variation in the inequality measure over time for the same country, one might still be worried that our results are driven by settings where the distribution is more polarized, as this would matter for the interpretation of the results.

[26]The index is constructed as $Polarization_c = 4\sum_{i=1}^{E} {}_c n_{i,c}^2(1 - n_{i,c})$ where $n_{i,c}$ is the relative size of ethnicity i in country c and E_c is the number of ethnic groups in the country. The measure describes how far the distribution of the ethnic group homelands is from a bipolar distribution. We also repeated the same analysis with 10 alternative measures of ethnic polarization and ethnic fractionalization, reported by Montalvo and Reynal-Querol (2005) and Posner (2004). Results are reported in Table C.5, in Appendix C. Despite the loss of observations, due to the fact that some countries are not covered by the original sources from which the indexes are taken, results are confirmed across all regressions.

[27]More specifically, our measure of National Rainfall Inequality (NRI) is computed for each country and year as $NRI = \frac{1}{2\bar{r}}\sum_{k=1}^{G}\sum_{l=1}^{G}\pi_k\pi_l \mid r_k - r_l \mid$, where G indicates the total number of rainfall gridcells covering the country, while π_k is the relative size of grid-cell k. As before, r_k is the amount of rain that fell over gridcell r, and $\bar{r}$ is the average amount of rain that fell over the whole country in that year.

remains large and significant.

Next, we show that our results are also robust to excluding main urban areas (regression 2)[28], restricting the sample to Sub-Saharan Africa (regression 3), and restricting the sample to the 17 countries that experienced at least one ethnic conflict over the period under investigation (regressions 4). We also check for outliers, by re-running our regression 42 times, dropping one country at a time. Despite the relatively small number of countries in the sample, the coefficient of interest remains stable, ranging from 0.488 to 0.818 (see Figure B.6, in Appendix B).

The inequality measures considered so far implicitly assume that more rainfall is always beneficial. While results in Table 3 support this link, it might still be that there are nonlinear effects. In regression 5 we therefore include a control for the share of ethnic groups in the country that received an unusually high amount of rain (i.e. 2 standard-deviations above the ethnic homeland average from 1982-2001). Also in this case the coefficient of interests remains large and significant.[29]

To further test the robustness of our result, we enrich our main specification with additional variables potentially related to ethnic conflict prevalence. First of all, conflicts tend to be persistent over time. Many empirical studies thus control for a lagged conflict variable. Regression 6 shows that lagged ethnic conflict is indeed a powerful predictor for current ethnic conflict, but the coefficient on the BGI measure remains virtually unaffected.[30]

Recent studies found that temperature can also have a direct impact on violence (Burke

[28]More specifically, we exclude from the original dataset all rainfall grids that contains (at least) one of the main African cities, as identified by ESRI (2000). The dataset has global coverage and can be downloaded from `http://techcenter.jefferson.kctcs.edu/data/` (Accessed: November 2015). The dataset contains 148 African cities, which include all national capitals, major population centers, and landmark cities.

[29]Results are confirmed whenever alternative measures are used, such as considering rainfall more than 1 standard-deviation above the average, considering an indicator for *at least* one ethnic group receiving "too much rain", or for the country as a whole receiving "too much rain" (results not reported, but available on request).

[30]The inclusion of the lagged dependent variable in a fixed effects model risks generating Nickell bias (Nickell, 1981). We therefore also re-estimated the regression using GMM estimators, instrumenting the first lag of the dependent variable with its second lag. The estimate of the coefficient of interest remains virtually unchanged (see regression 3 in Table C.4, in Appendix C).

et al., 2009; Ranson, 2014). Given the correlation across climatic factors and to avoid any omitted variables bias, Burke et al. (2015) recommend considering both rainfall and temperature measures in any empirical study of climate and conflicts. In regression 7 we therefore control for a between-group inequality measure constructed using temperature data. The coefficient on the temperature-related measure is positive – although far from significance – and, importantly, our coefficient of interest remains very stable.

Recent studies further suggest two other channels through which rainfall might affect conflict prevalence: a) rainfall might increase transportation cost and thus decrease chances that troops meet in combat (Rogall, 2014); and b) rain might provide more fertile ground for malaria parasites and vector (Kudamatsu et al., 2014), thus affecting the physical strength of individuals – although in this case the effect on the risk of conflict is more ambiguous. Reassuringly, regression 8 shows that our results are robust to including a measure of yearly rainfall along the main roads of each country as well as the climate index for malaria prevalence.

We then check how the impact of the rainfall-based inequality measure compares to standard measures of rainfall shocks used in the literature. In their seminal paper, Miguel et al. (2004) consider current and lagged country-wide measures of rainfall growth, finding that a drop in rainfall translates into a significantly higher likelihood of civil conflicts. We replicate their measures with our rainfall data – which come at higher resolution – and include them in the same regression with the current and lagged BGRI measures. Results in regression 4 show that the coefficients on the two rainfall growth variables are negative, as expected, but far from statistical significance, while the coefficients of both the current and lagged BGRI measures remain large and significant. These results indicate that, within our sample, variation in the distribution of rainfall across ethnic groups is a more relevant determinant of ethnic conflicts than country-wide variation in rainfall.[31]

[31]Similarly to what we did in Table 2 and in order to preserve the number of observations, when constructing the lagged inequality measure for the first year in the sample (1982) we assume that the growing season in the previous year (1981) was the same as the average growing season over the period 1982-2001. Results remain virtually unaffected if the first year is instead excluded from the analysis (see regressions 4

In Appendix D, we describe a number of additional robustness checks. In particular, our results also robust to: 1) extending the analysis to bracket the period 1960-2001 [32]; 2) controlling for rainfall inequality *within* ethnic groups; 3) adding a rich set of additional controls, such as GDP, institutional quality, natural resource, and neighboring countries conditions; 4) considering conflict onset rather than conflict prevalence.

4.2.4. The Role of Ethnic Power Relationships

So far, we have shown that exogenous changes in the distribution of resources across ethnic groups significantly affects the risk of ethnic violence. To better understand the mechanisms, we study how the observed relationship depends on the political power distribution. In order to do so, we rely on the information on the level of political power of the different ethnic groups contained in the EPR dataset. As a very first step, we check that our previous results are confirmed when we build our dataset using the EPR dataset and the corresponding GeoEPR maps, which, as mentioned in the data section, have smaller coverage and a somewhat different definition of ethnic groups.[33]. Table 7 reports the estimates. Although we lose more than 15% of the country-year observations compared to the initial analysis, regression 1 shows that the estimated coefficient on BGRI is still significant at 10% level (p-value=0.073), and very close in magnitude to what we obtained with the GREG dataset (0.662). Also in this case, when we perform the main check based on the timing of the growing season, we see that rainfall outside the season has no effect on conflict prevalence (regression 2).

We next take ethnic power relations into account. We are specifically interested in understanding whether and how rainfall inequality interacts with political inequality. We

and 5 in Table C.4, in Appendix C). Results are moreover confirmed when instead of rainfall growth we use alternative measures such as rainfall levels or deviations from the country mean (see regressions 6 and 7 in Table C.4, in Appendix C).

[32]Given that information on the vegetation index only starts in 1982, in performing this check we assume that the growing season over the period 1960-1981 was the same as the average growing season observed during the period 1982-2001.

[33]The number of countries and ethnicities decreases to 37 and 172, respectively. For more details, see Table **??**, in Appendix C.

therefore identify the *leading* group within a country as the one that either rules alone (i.e. is *Dominant* or *Monopolist*) or is *Senior Partner* in settings where a power sharing agreement is in place.[34] We then recalculate our BGRI measure by only summing absolute rainfall differences between the leading ethnic group in the country and the other groups We then rerun model (2) considering this power-adjusted inequality measure.

Regression 3 shows that the new measure has a large and significant effect on ethnic conflict prevalence (1.074, p-value=0.01). A horse-race between the new measure and the original BGRI strikingly shows that inequality with respect to the leading group is what drives the results: the coefficient of the original BGRI becomes virtually zero (0.007, p-value=0.988), while the coefficient of the power-based inequality measure remains large and highly significant (1.071, p-value=0.035).[35] Finally, in regression 4 we test the new between-group inequality measure, based on political power relations, against an alternative measure, in which the most powerful group is defined on the basis of population size – a possible alternative measure of the group's strength. The estimates clearly confirm that it is access to power that matters.

5. Analysis by Ethnicity

5.1. Empirical Framework

The analysis at country level does not allow us to disentangle individual groups' behavior. As a further step, we analyze the interaction between rainfall inequality and political power at the ethnic group level. The analysis is again based on the EPR dataset and the

[34]Most of the countries in the sample have one and only one main ethnic group defined in this way for each year. There are only few exceptions. Zambia is the only country to have multiple Senior Partners, and we therefore exclude it from the analysis. Sierra Leone and Liberia are recorded as Collapsed States – and hence without information on access to executive power – for 8 and 7 years, respectively, while Gambia has only information for non-main ethnic groups for 8 years. These country-years are therefore also excluded from the analysis.

[35]The correlation between the standard BGRI measure and the power-based measure is 0.7 (see Table C.3, in Appendix C).

corresponding GeoEPR maps. In this case we build a group-specific measure of *Rainfall Inequality* (RI) with respect to the leading ethnic group in the country, which we model on the basis of the country-level inequality measure described above and define as

$$RI_i^{power} = \frac{1}{\bar{r}} \mid r^{LEAD} - r_i \mid \tag{3}$$

where, again, r_i indicates the amount of rainfall during the growing season within the boundaries of ethnic group i, while r^{LEAD} indicates the amount of rainfall within the boundaries of the leading ethnic group. As before, the measure is normalized using the average level of rainfall within the country. We then run the following empirical model:

$$EthnicConflict_{i,c,t} = \delta RI_{i,c,t}^{power} + \Omega \mathbf{C}_{i,c,t} + \varrho_i + \zeta_c + \upsilon_t + \varpi_c t + \xi_{i,c,t} \tag{4}$$

where the dependent variable is an indicator taking on the value of 1 if there is a rebel group fighting the central state in the name of ethnicity i in country c and yeat t. $\mathbf{C}$ includes a set of controls at the ethnicity level that will be detailed below. Finally, ϱ_i, ζ_c, and υ_t represent ethnicity, country, and year fixed effects, while $\varpi_c t$ represents country-specific time trends. Compared to the model used for the analysis at the country-level, the inclusion of a full set of ethnicity fixed effects allows us to take into account any time-invariant ethnic-specific characteristic. Following Cederman et al. (2011), in running this analysis we exclude ethnic groups that are recorded as ruling alone (i.e. *Monopolist* or *Dominant*), because, by definition, they can never be linked to any rebel group involved in a civil conflict against the central government.[36] This also simplifies the interpretation of the coefficient of interest δ: a positive coefficient indicates that a larger gap in rainfall between ethnic group i and the *leading* group leads to a higher chance that ethnic group i

[36]These groups indeed never appear involved in any ethnic civil conflict in the EPR dataset. As explained above, we include in our definition of leading ethnic group also groups classified as *Senior Partner*. There is one instance in the dataset in which one such group is recorded as fighting a civil conflict against the central government and we therefore keep also this category in the analysis, By construction, for *Senior Partner* groups the inequality measures with respect to the leading group always take value 0.

is involved in an ethnic conflict against the central state.

Finally, to tease out the mechanism and distinguish the two cases in which a group receives more or less rain than the leading group, we split the inequality measure in two:

$$RI_i^{power-} = \begin{cases} \frac{1}{\bar{r}}(r^{LEAD} - r_i) & \text{if } r^{LEAD} > r_i \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

$$RI_i^{power+} = \begin{cases} \frac{1}{\bar{r}}(r_i - r^{LEAD}) & \text{if } r^{LEAD} < r_i \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

and we re-run empirical model (4) replacing $\delta RI_{i,c,t}^{power}$ with the two terms $\delta_1 RI_{i,c,t}^{power-}$ and $\delta_2 RI_{i,c,t}^{power+}$.

5.2. Results

Results are reported in Table 8. Albeit significant only at 10%, the estimate in regression 1 is in line with the result observed at the country-level and confirms the importance of power relationships between ethnic groups. The coefficient indicates that one standard-deviation increase in rainfall inequality with respect to the leading ethnic group leads to a 3.5 percentage point (or 0.12 standard-deviation) increase in the likelihood that the group is involved in an ethnic civil conflict. This translates in a 39% increase compared to the average conflict prevalence across the sample (9%).

When we split the measure into positive and negative differences in rainfall, we find that an ethnic group is more likely to fight in an ethnic conflict when it receives relatively *less* rain (regression 2). On the contrary, receiving *more* rain does not lead to significantly higher conflict prevalence (regression 3). Results are confirmed when the two measures are jointly included in the same regression (regression 4).[37]

5.2.1. Robustness Checks

Regression 5 shows that our result is robust to including a number of additional controls: whether the group lost power in the previous year, whether the group is fully excluded from power, and the number of conflicts the group was previously involved in (since its record in the EPR dataset). In line with previous findings in the literature, all these variables significantly increase the chances that a group engages in ethnic conflict (Cederman et al., 2010). We also include a variable capturing group-specific variations in rainfall with respect to its average over the period 1982-2001, expressed in standard-deviation units. This is meant to capture the effect of local variations in rainfall. While the coefficient on this variable is negative, as expected, it is far from reaching statistical significance.[38] To further assess the robustness of our finding, we also repeat the analysis (for regression 4) dropping each country from the sample, one at a time. Despite the relatively small number of countries available, the estimated coefficient for our variable of interest remains stable, ranging from 0.052 to 0.113 (Figure B.7 in Appendix B). [39]

5.2.2. Channels

Recent evidence from Africa shows that political representation is often used as an instrument to manage ethnic relations (Francois et al., 2015). We therefore split the sample

[37]A Wald test confirms that we can rejects the hypothesis that the two coefficients are the same, at the 10% confidence level (p-value=0.057).

[38]We also run a regression controlling for a group-specific measure of oil and gas inequality. Following Morelli and Rohner (2015), we construct the variable as the share of a country's surface covered with oil and gas that falls within the ethnic group's territory. Despite losing almost half of the observations, our results are confirmed, while the coefficient of the oil and gas inequality variable is positive and significant, as predicted by the authors (see regression 1 of Table C.6, in Appendix C).

[39]Table C.6 in Appendix C includes two additional robustness checks. First, we account for the fact that too much rainfall during the growing season is likely to be detrimental by including a control for the leading group in the country receiving an amount of rainfall more than 2 standard-deviations above its average level over the period 1982-2011 (regression 2). Second, we extend the analysis back to 1960, assuming that the growing season before 1982 was the same as the average growing season over the period 1982-2001 (regression 3). Our results are once again confirmed.

between ethnic groups with some access to political power and groups that are instead fully excluded from power, to see whether political representation reduces the risk that rising resource inequality conduce to violence. Results reported in Table 8 indicate that this is indeed the case. We find no effects of rainfall inequality for ethnic groups that are *Junior Partners* (regression 6), while we see a positive and significant effect for groups fully excluded from power (regression 7), whenever they receive relatively less rain than the leading group.

This result appears consistent with the relative drop in resources both exacerbating grievances and making the conflict relatively cheaper (i.e. opportunity cost channel) for the excluded group. To shed more light on which channel might dominate we provide two indirect tests.

First we focus on groups that recently lost political power. Grievances are likely high in these cases and, if an exogenous rise in inequality further exacerbates them, we should expect a particularly large effect on conflict. This is indeed what we observe in the data. In regression 8 we interact the RI_i^{power-} measure with an indicator variable for whether the ethnic group has been "downgraded" in the previous year in the power scale provided by the EPR dataset.[40] The interaction coefficient is positive and highly significant.[41]

Allegedly, this result could still be consistent with a pure opportunity-cost mechanism, as the recently downgraded ethnic group might also find it easier to mobilize group members to fight as a consequence of the relative drop in resources. However, if opportunity-cost considerations were the driving force, the effect should be strongest when the non-leading group not only receives less rain than the leading group, but also less rain than its usual level. Indeed, while for the *relative deprivation* theory (Gurr, 1970)

[40] From the most to the least powerful group, the scale goes: *Monopolist*, *Dominant*, *Senior Partner*, *Junior Partner*, *Powerless*, *Discriminated*.

[41] Table C.6, in Appendix C, shows that results are confirmed when also interaction terms for RI_i^{power+} are included in the same regression (regression 2), when we use an alternative indicator variable for having been downgraded from having at least some power (i.e. *Junior Partner* or above) to having no power at all (i.e. *Powerless* or below) (regression 3), and when using an indicator that takes into account any downgrading that happened in the previous 5 years (regression 4).

what matters is resource availability in relation to the other (leading) group, the ability to mobilize masses for violence on the basis of opportunity-cost considerations should improve as the level of available resources decreases (i.e. as there is less to lose) – *ceteris paribus*. In regression 9 we therefore include a triple interaction term, in which we interact the RI_i^{power-} measure and the "downgraded" indicator with the variable capturing ethnic-specific variations in rainfall with respect to its average over the period 1982-2001 (expressed in standard-deviation units). All double interaction terms are also included in the regression and reported in regression 9. While the double interaction term between RI_i^{power-} and the "downgraded" indicator remains large and significant, the triple interaction term is not. This indicates that larger resource gaps with respect to the leading group are likely to lead to higher conflict prevalence, irrespectively of the local condition of the ethnic group.[42] Although, allegedly, these two tests do not allow us to unequivocally pin down the mechanism, they do suggest that grievances are likely to play an important role in explaining the observed relationship between resource inequality and conflict.

Overall, the results of the analysis at the (country-)ethnicity level confirm that rainfall-based inequality is a strong predictor of ethnic conflict. They also show that the link between inequality and conflict strongly depends on the specific power relations among the different ethnic groups. In particular, the estimates are consistent with inequality leading to higher conflict prevalence by exacerbating grievances in ethnic groups excluded from political power.

[42]Table C.6, in Appendix C, shows that the result is confirmed when considering the simple interaction between RI_i^{power-} and the variable capturing ethnic-specific variations in rainfall expressed in SD (regression 5), when also all double and triple interaction terms for RI_i^{power+} are included in the same regression (regression 6), and when the variable capturing ethnic-specific variations in rainfall expressed in SD units is replaced with a simple indicator variable for the ethnic group receiving less rainfall than its average over the study period (regression 7).

6. Discussion and Conclusion

In this paper we use high-frequency spatially disaggregated rainfall data to construct a new measure of inequality between ethnic groups living within the same country. The full sample includes 214 ethnicities, located across 42 African countries, and covers the time period 1982-2001. Our main result shows that a one standard-deviation increase in rainfall-based inequality increases ethnic conflict prevalence by 16 percentage points (or 0.43 standard-deviations). The result is driven by rainfall during the plant-growing season and is robust across a large set of placebo tests and robustness checks.

We also find that political inequality interacts with rainfall inequality in leading to ethnic conflict. Combining the analysis at the country level and at the ethnicity level, we find that a more unequal distribution of rainfall is likely to spur ethnic violence whenever it penalizes ethnic groups with no access to executive power. The effect is strongest when the penalized group recently lost its power. Although with the data at our disposal we are not able to isolate the exact mechanism, our findings suggest that rising grievances in the excluded ethnic groups are an important force behind the observed relationship between resource inequality and conflict.

Overall, our results provide an important contribution to the long-standing debate concerning the role of inequality as a determinant of civil conflicts. By relying on a new exogenous measure, we are able to circumvent the limitations that have affected previous empirical studies and provide strong and robust evidence of the causal link. We also contribute to the recent and fast-growing literature on climate and conflict, by showing the importance of the distribution of climatic variables within a country, over and above their local impact. Finally, we provide evidence that the link between inequality and conflict strongly depends on the specific power relations among the different ethnic groups.

Our findings indicate that actions should be taken to prevent that an increase in the variability of weather conditions, related to climate change patterns, could lead to a further increase in ethnic conflicts across the African continent. Although further analysis will be needed to identify the most appropriate response, the evidence presented in this paper suggests that building more resilient agricultural systems that are less dependent on rainfall – for instance by strengthening irrigation systems – has the potential to reduce ethnic conflict prevalence. Redistributive policies that provide compensation for groups and areas penalized by the weather could also help reducing the risk of violence. On top of this, the results presented in this paper show that political representation is a powerful tool for settling ethnic tensions and for mitigating the risk that rising grievances across ethnic groups degenerate in armed violence.

Finally, our analysis represents a call for more and better data. While by combining different data sources in an innovative way we were able to circumvent the lack of disaggregated income data, our analysis would certainly benefit from the availability of more direct measures. The constant improvement in data collection methods will hopefully make available such measures in the near future, allowing us to further develop the findings presented here.

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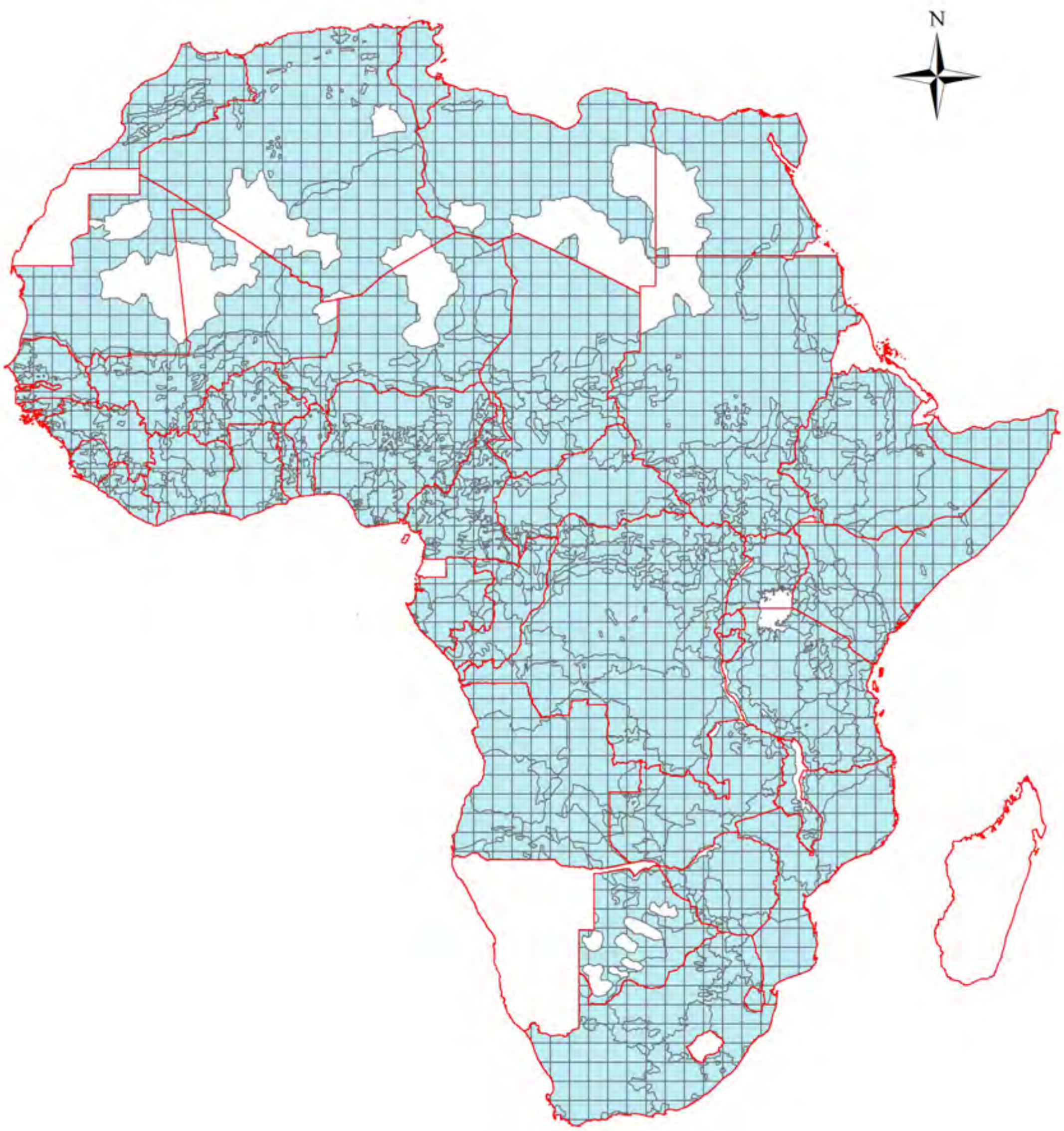
FIGURES & TABLES

Figure 1: Dataset construction – GREG



Notes: The figure shows how the dataset has been constructed, by spatially merging three different maps: the ECMWF rainfall grid of 1.25×1.25 degree cells, the GREG map of ethnic homeland boundaries (gray lines), and an administrative map of Africa (red lines). Areas in white are excluded from the analysis: Lesotho and Madagascar are excluded because they only host one ethnic homeland; Eritrea and Namibia are excluded because the two countries only became independent during the period under consideration; other white areas indicate that no ethnic group was recorded there.

Table 1: Summary statistics – Country-Level Analysis

	Mean	Min	Max	Std.dev.	Obs
PANEL 1: Country-Level Measures					
A. Conflict					
Civil Conflict	0.25	0.00	1.00	0.43	840
Ethnic Conflict	0.18	0.00	1.00	0.38	840
B. Inequality Variables					
BGRI, growing season	0.23	0.00	1.00	0.23	840
BGRI, non-growing season	0.35	0.00	1.00	0.23	840
BGRI, growing season, adm units	0.34	0.00	1.00	0.26	840
BGRI, growing season, SDs	0.21	0.00	1.00	0.17	840
BGRI, growing season, no cities	0.23	0.00	1.00	0.23	840
BGI, growing season, temperature	0.19	0.00	1.00	0.19	840
BGNI	0.34	0.00	1.00	0.26	420
NRI, growing season	0.34	0.00	1.00	0.24	840
BGRI, growing season (EPR)	0.19	0.00	1.00	0.21	746
BGRI, non-growing season (EPR)	0.33	0.00	1.00	0.24	746
BGRI^{power}, growing season	0.13	0.00	1.00	0.18	737
BGRI^{size}, growing season	0.15	0.00	1.00	0.19	760
C. Other Control Variables					
Cereals, gross production index	76.86	18.63	305.48	36.42	829
Crops, gross production index	70.11	25.19	155.81	21.40	829
Agriculture, gross production index	69.65	28.23	131.51	18.54	829
Food, gross production index	69.27	28.07	128.75	18.35	829
Avg rainfall, growing season	28.55	0.04	125.54	25.21	840
Rainfall growth, growing season	0.03	−0.70	2.90	0.31	840
Share groups with rain>2SD	0.04	0.00	0.75	0.10	840
Avg rainfall along main roads	33.70	0.06	139.01	29.22	840
Malaria prevalence index	0.58	0.00	1.00	0.34	840
PANEL 2: Ethnicity-Level Measures					
A. Conflict					
Ethnic Conflict	0.09	0.00	1.00	0.29	2995
B. Inequality Variables					
RI^{power}, growing season	0.66	0.00	9.25	1.05	2995
RI^{power-}, growing season	0.21	0.00	5.52	0.54	2995
RI^{power+}, growing season	0.45	0.00	9.25	1.01	2995
C. Other Control Variables					
Downgraded	0.02	0.00	1.00	0.13	2995
Excluded Group	0.52	0.00	1.00	0.50	2995
Rainfall SD, growing season	−0.13	−2.25	3.75	0.93	2995
Number of past conflicts	0.25	0.00	5.00	0.58	2995

Notes: ***Panel 1*** includes all variables used for the analysis at the country level. All inequality measures have been normalized by taking $(X - X_{min})/(X_{max} - X_{min})$. **BGRI** is Between-Group Rainfall Inequality. **BGNI** is Between-Group Nightlight Inequality **NRI** is National Rainfall Inequality. ***Adm units*** indicates that the measure was computed considering administrative borders. ***SDs*** indicates that the measure was computed comparing yearly deviations from each ethnic-group average rainfall. ***No cities*** indicates that areas where main cities are located were excluded. ***Temperature*** indicates that the measure refers to inequality in temperature. **EPR** indicates that the measure is based on the GeoEPR maps, rather than the GREG ones. **BGRI**^{power} indicates that the inequality measure is constructed with respect to the rainfall received by the *leading* ethnic group in the country. **BGRI**^{size} indicates that the inequality measure is constructed with respect to the rainfall received by the ethnic group with the largest population. The full sample include 42 countries over the period 1982-2001. ***Panel 2*** includes all variables used for the analysis at the ethnicity level. **RI**^{power} indicates rainfall inequality between the specific ethnic group and the *leading* group. **RI**$^{power+}$ (**RI**$^{power-}$) is equal to RI^{power} when the ethnic group receives more (less) rainfall then the *leading* group, and zero otherwise. **Group lost power** is an indicator that takes on the value of 1 when the ethnic group has been downgraded in the power scale provided in the EPR dataset. **Excluded Group** is an indicator that takes on the value of 1 when the group has no access to power. The sample includes 172 ethnic groups, 37 countries and 20 years (1982-2001). For more details and sources, see the main text.

Table 2: Main effects at the country level

Dependent Variable:	Ethnic Conflict				
	(1)	(2)	(3)	(4)	(5)
BGRI, growing season	0.338*	0.706**	0.658**	0.715**	
	(0.184)	(0.316)	(0.307)	(0.326)	
BGRI, growing season (t-1)			0.482**		
			(0.195)		
BGRI, growing season (t-2)			0.446		
			(0.295)		
Avg rainfall, growing season (log)				0.020	
				(0.063)	
BGRI, growing season, SDs					0.196**
					(0.084)
Country Effects	no	yes	yes	yes	yes
Year Effects	no	yes	yes	yes	yes
Country Time Trends	no	yes	yes	yes	yes
R^2	0.04	0.70	0.71	0.70	0.70
N	840	840	840	840	840

Note: All inequality measures have been normalized by taking $(X - X_{min})/(X_{max} - X_{min})$. **Ethnic Conflict** is an indicator variable that takes on the value of 1 if a country experienced ethnic conflict in a given year. **BGRI** indicates Between-Group Rainfall Inequality. ***SDs*** indicates that the inequality measure was computed comparing yearly deviations from each ethnic-group average rainfall, instead than comparing rainfall levels. The sample includes 42 African countries and 20 years (1982-2001). Two-way clustered standard errors by year and country in parentheses, adjusted for low number of clusters, using the number of years. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 3: Validation check

Dependent Variable:	Cereals Gross Production Index		Crops Gross Production Index		Agriculture Gross Production Index		Food Gross Production Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg rainfall, growing season (log)	14.091*	17.077*	8.723**	8.479**	5.485**	4.712**	5.402**	4.535**
	(7.070)	(8.228)	(3.052)	(2.972)	(1.982)	(1.912)	(2.012)	(1.951)
Avg rainfall, non-growing season (log)		−3.750		0.307		0.971		1.089
		(3.828)		(1.045)		(0.742)		(0.814)
Country Effects	yes	yes	yes	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes	yes	yes	yes
Country Time Trends	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.64	0.64	0.86	0.86	0.89	0.89	0.89	0.89
N	829	829	829	829	829	829	829	829

Note: Production indexes are taken from FAO and record the relative level of the aggregate volume of production for each year in comparison with the base period 2004-2006. They include the quantities of the commodity sold in the market (marketed production) and the quantities consumed or used by the producers (auto-consumption). When calculating indexes of agricultural and food production, all intermediate primary inputs of agricultural origin are deducted. The category of food production includes commodities that are considered edible and that contain nutrients and includes commodities derived as a result of further processing. The sample includes available data for 42 African countries and 20 years (1982-2001). Two-way clustered standard errors by year and country in parentheses, adjusted for low number of clusters, using the number of years. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Nightlight density, 1992-2001

Dependent Variable:	Nightlight density (log)		BGNI		
	(1)	(2)	(3)	(4)	(5)
Avg rainfall, growing season (log)	0.045*	0.049			
	(0.023)	(0.027)			
Avg rainfall, non-growing season (log)		−0.015			
		(0.018)			
BGRI, growing season			0.062**	0.058**	0.066**
			(0.024)	(0.019)	(0.026)
BGRI, non-growing season				0.016	
				(0.021)	
BGRI, growing season (t-1)					0.113
					(0.079)
Ethnicity Effects	yes	yes	no	no	no
Country Effects	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes
Country Time Trends	yes	yes	yes	yes	yes
R^2	0.88	0.88	0.99	0.99	0.99
N	5137	5137	420	420	420

Note: All inequality measures have been normalized by taking $(X - X_{min})/(X_{max} - X_{min})$. **BGNI** measures Between-Group Nightlight Inequality. **BGRI** indicates Between-Group Rainfall Inequality. The analysis in columns 1 and 2 considers an ethnicity in a given country in a given year as the unit of observation. The analysis in columns 3 to 5 is instead aggregated at the country-year level. Overall the sample includes 214 ethnicities, 42 African countries, and 10 years (1992-2001). Two-way clustered standard errors by year and country in parentheses, adjusted for low number of clusters, using the number of years. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5: Falsification tests

Dependent Variable:	Ethnic Conflict						Non-Ethnic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BGRI, growing season	0.734**		0.697**		0.789**		−0.239
	(0.324)		(0.304)		(0.296)		(0.178)
BGRI, non-growing season	−0.153	−0.130					
	(0.130)	(0.134)					
BGRI, growing season (t+1)			0.103	0.193			
			(0.266)	(0.296)			
BGRI, growing season, adm units					−0.084	0.272	
					(0.098)	(0.186)	
Country Effects	yes	yes	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes	yes	yes
Country Time Trends	yes	yes	yes	yes	yes	yes	yes
R^2	0.70	0.70	0.70	0.70	0.70	0.70	0.66
N	840	840	840	840	840	840	840

Note: All inequality measures have been normalized by taking $(X - X_{min})/(X_{max} - X_{min})$. **Ethnic Conflict** is an indicator variable that takes on the value of 1 if a country experienced ethnic conflict in a given year. **BGRI** indicates Between-Group Rainfall Inequality. ***Non-growing season*** indicates that the inequality measure is based on rainfall outside the growing season. ***Adm units*** indicates that the inequality measure was computed considering level 1 administrative borders rather than ethnic homeland's boundaries. **Non-Ethnic** is an indicator variable that takes on the value of 1 if a country experienced a non-ethnic conflict in a given year. The full sample includes 42 African countries and 20 years (1982-2001). Two-way clustered standard errors by year and country in parentheses, adjusted for low number of clusters, using the number of years. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 6: Robustness checks

Dependent Variable:	Ethnic Conflict								
	Polariz	Exclude Cities	Only SSA	Only variation	Excessive rainfall	Additional Controls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BGRI, growing season	0.888**	0.675**	0.803**	1.470**	0.735**	0.635**	0.717**	0.710**	0.621*
	(0.323)	(0.315)	(0.345)	(0.567)	(0.315)	(0.288)	(0.309)	(0.324)	(0.303)
NRI, growing season	−0.129								
	(0.116)								
NRI × Polarization	−0.183								
	(0.292)								
Share groups with rain>2SD					0.171				
					(0.107)				
Ethnic Conflict (t-1)						0.312***			
						(0.087)			
BGI, growing season, temperature							0.370		
							(0.627)		
Malaria prevalence index								0.145	
								(0.165)	
Avg rainfall along main roads (log)								0.024	
								(0.068)	
BGRI, growing season (t-1)									0.546**
									(0.227)
Rainfall growth, growing season									−0.029
									(0.031)
Rainfall growth, growing season (t-1)									−0.030
									(0.031)
Country Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country Time Trends	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.70	0.70	0.69	0.56	0.70	0.73	0.70	0.70	0.70
N	840	840	740	340	840	840	840	840	840

Note: All inequality measures have been normalized by taking $(X - X_{min})/(X_{max} - X_{min})$. **Ethnic Conflict** is an indicator variable that takes on the value of 1 if a country experienced ethnic conflict in a given year. **BGRI** indicates Between-Group Rainfall Inequality. **NRI** indicates National Rainfall Inequality. ***Temperature*** indicates that the inequality measure refers to inequality in temperature, rather than in rainfall. The polarization index used in column (1) is constructed following Montalvo and Reynal-Querol (2005). ***No cities*** indicates that areas where (at least) one of the main cities is located were excluded from the analysis. Column (3) only includes 37 Sub-Saharan countries. Column (4) only considers 17 countries for which there is variation in the dependent variable. **Share groups with rain>2SD** captures the share of ethnic groups that received an amount of rain during the growing season that is more than 2 standard-deviations above the average amount they received during the period 1982-2001. The full sample includes 42 African countries and 20 years (1982-2001). Two-way clustered standard errors by year and country in parentheses, adjusted for low number of clusters, using the number of years. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7: Ethnic Power Relations – Country level

Dependent Variable:	Ethnic Conflict				
	(1)	(2)	(3)	(4)	(5)
BGRI, growing season (EPR)	0.662*	0.713*		0.007	
	(0.348)	(0.354)		(0.497)	
BGRI, non-growing season (EPR)		−0.198			
		(0.140)			
BGRI^{power}, growing season			1.074***	1.071**	1.165**
			(0.374)	(0.471)	(0.423)
BGRI^{size}, growing season					−0.268
					(0.403)
Country Effects	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes
Country Time Trends	yes	yes	yes	yes	yes
R^2	0.71	0.72	0.73	0.73	0.73
N	702	702	702	702	702

Note: All inequality measures have been normalized by taking $(X - X_{min})/(X_{max} - X_{min})$. The dependent variable **Ethnic Conflict** is an indicator variable that takes on the value of 1 if a country experienced ethnic conflict in a given year. **BGRI** indicates Between-Group Rainfall Inequality. **BGRI**^{power} indicates that the inequality measure is constructed with respect to the rainfall received by the leading ethnic group – meaning the ethnic group that is classified in the EPR dataset as *Monopolist*, *Dominant* or *Senior Partner*. **BGRI**^{size} indicates that the inequality measure is constructed with respect to the rainfall received by the ethnic group with the largest population. The sample includes 37 African countries and 20 years (1982-2001). Missing observations are due to the absence of *leading* ethnic groups for some specific years in some countries. Two-way clustered standard errors by year and country in parentheses, adjusted for low number of clusters, using the number of years. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 8: Ethnic Power Relations – Ethnicity Level

Dependent Variable:	Rebel group fighting in the name of the ethnic group								
Sample:	Full					*Junior P.*	*Excluded*	*Full*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RI^{power}, growing season	0.033*								
	(0.016)								
RI^{power-}, growing season		0.075**		0.076**	0.073**	−0.005	0.062**	0.061**	0.064**
		(0.033)		(0.034)	(0.029)	(0.036)	(0.026)	(0.024)	(0.027)
RI^{power+}, growing season			0.010	0.011	0.013	0.004	0.010		
			(0.011)	(0.011)	(0.012)	(0.006)	(0.007)		
Downgrade × RI^{power-}								0.250***	0.257***
								(0.057)	(0.063)
Downgraded × RI^{power-} × RainfallSD									0.054
									(0.037)
Downgraded × RainfallSD									−0.037
									(0.032)
RI^{power-} × RainfallSD									0.005
									(0.012)
Downgraded					0.101*			0.009	0.009
					(0.055)			(0.036)	(0.039)
Excluded Group					0.078**				
					(0.037)				
RainfallSD					−0.004				−0.004
					(0.005)				(0.006)
Number of past conflicts					0.177**				
					(0.081)				
Ethnicity Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country Time Trends	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.70	0.70	0.69	0.70	0.72	0.44	0.76	0.70	0.71
Ethnicities	172	172	172	172	172	91	104	172	172
Countries	37	37	37	37	37	29	32	37	37
N	2995	2995	2995	2995	2995	1036	1543	2995	2995

Note: The dependent variable is an indicator that takes on the value of 1 if there is a rebel group fighting the central state in the name of the ethnic group. Groups ruling alone – i.e. recorded as *Monopolist* or *Dominant* in the EPR dataset – are excluded because by definition they cannot be fighting the central state. **RI^{power}** indicates Rainfall Inequality between an ethnic group and the *leading* group, normalized by the average rainfall in the country. **RI^{power+}** (**RI^{power-}**) is equal to RI^{power} when the ethnic group receives more (less) rainfall then the *leading* group, and zero otherwise. **Downgraded** is an indicator variable that takes on the value of 1 when the ethnic group was downgraded in the power scale provided in the EPR dataset. From the most to the least powerful group, the scale goes: *Monopolist*, *Dominant*, *Senior Partner*, *Junior Partner*, *Powerless*, *Discriminated*. **Excluded Group** is an indicator variable that takes on the value of 1 when the group is ranked *Powerless* or below. **RainfallSD** records variation in rainfall during the growing season with respect to the ethnic-specific average over the period 1982-2001 (expressed in SD units). In regressions (6) the sample is restricted to *Junior Partners*. In regressions (7) the sample is restricted to *Excluded Group*. The full sample includes 172 ethnic groups, 37 countries, and 20 years (1982-2001). Two-way clustered standard errors by year and country in parentheses, adjusted for low number of clusters, using the number of years. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix A – Data

In this appendix we describe more in details the data sources we use for our analysis and the way we built the variables. The exposition mirrors the structure followed in Section 3, in the main text.

A.1. Key variables

Conflicts To construct our dependent variable we rely on the Ethnic Armed Conflict (EAC) dataset provided by Wimmer et al. (2009). The dataset builds on the conflicts recorded by the Armed Conflict Data database developed by the International Peace Research Institute of Oslo and the University of Uppsala (Gleditsch et al., 2002). The PRIO/Uppsala database records all conflicts with a threshold of 25 battle deaths per year, since 1946. An armed conflict 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 within a year. The dataset records information at the country level on a yearly basis and, among other things, it distinguishes between civil and interstate conflicts. For each civil conflict included in the PRIO/Uppsala database the EAC dataset identifies whether: 1) the armed organizations involved explicitly pursued ethno-nationalist aims, motivations, and interests and 2) they recruited fighters and forged alliances on the basis of ethnic affiliations.[1] We generate an indicator variable for the presence of an ethnic conflict in a country in a given year, if the two conditions listed above are fulfilled.[2]

Ethnicity Ethnic group information stems from the Geo-Referencing of Ethnic Group (GREG) map provided by Weidman et al. (2010). The map was created by digitalizing and merging the 57 maps that constitute the*Soviet Atlas Narodov Mira* (1964), which describe the spatial distribution of 928 ethnic groups around the world as of the early 60s. The *Soviet Atlas* combines a number of different sources, such as population census data, ethnographic publications of government agencies and geographic maps assembled by the institute of Ethnography at the USSR Academy of Science. Although there is no

[1]We rely on the EAC version based on the 3-2005b version of the PRIO/Uppsala data set. There are few discrepancies between the two dataset: 1) the EAC dataset does not cover small states, such as Djibouti, Comoros and Equatorial Guinea, which are in any case excluded from our analysis; 2) the EAC dataset does not consider as civil conflicts the 1975-1989 conflict in West Sahara (a territory not recognized in the COW state system), the 1966-1988 conflict in South Africa (as it is the Namibian war of independence) and the 1962-1991 conflict in Ethiopia (as it is the Eritrean war of independence), which are therefore also excluded from our analysis; 3) there are few changes in the coding of conflicts in Chad, as in the EAC dataset 1979, 1985 and 1986 are not considered as conflict years, while they are in the PRIO/Uppsala database, and also in this case we follow the EAC approach for consistency; 4) there are few changes in the sub-IDs coding that took place in the EAC dataset, which we are able to harmonize thanks to the support kindly provided by Brian Min.

[2]This is the same criterion used by the authors to define an ethnic conflict. The two conditions are in any case always jointly satisfied, with the only exception of Ethiopia between 1996 and 1999, when only condition 1 is satisfied. Considering this conflict as ethnic leaves our results unaffected (results available on request).

official definition of ethnic group in the original dataset, the classification has been recently validated by looking at ethnic intermarriages: ethnic groups defined in the Atlas are mostly endogamous, although in some cases further endogamous subgroups could be identified – i.e. ethnic divisions appears to be underreported (Bridgman, 2008). Our dataset includes 214 different ethnicities, with an average of 11 (median is 10) different ethnicities per country (see Table C.1). Whenever an area is assigned to multiple ethnicities, we assume them as having equal size over that area.

In the second part of our analysis we replicate our main result with an alternative *dynamic* set of digitalized maps, provided by Wucherpfennig et al. (2011). The Georeferencing Ethnic Power Relations (GeoEPR) maps trace the location of the ethnic groups included in the EPR dataset (see below) over time. The classification and localization of ethnic groups is based on expert panels and is somewhat different from those adopted in the GREG map. The GeoEPR set of maps has the advantage of being dynamic, it also has smaller coverage than the GREG map.

Ethnic Power Relations Information on the power relationships across ethnic groups is taken from the Ethnic Power Relations (EPR) dataset provided by Girardin et al. (2015). The dataset contains disaggregated information on all politically relevant ethnic groups within a country, including their estimated size and their level of access to state executive power. As mentioned above, the classification of ethnic groups is based on expert panel and is somewhat different from the one adopted in the *Soviet Atlas*.[3] Whenever using the EPR dataset we therefore rely on the GeoEPR map provided by Wucherpfennig and co-authors (2011).

The EPR dataset classifies each politically relevant ethnic group into one of three main categories of access to executive power, each one composed by two sub-categories. First, an ethnic group can rule alone, as a *Monopolist* or a *Dominant* group, depending on whether there is space for limited inclusion of other parties in the executive body or not. Second, a group can formally or informally share executive power with other ethnic groups, being either a *Senior Partner* or a *Junior Partner* in the arrangement. Finally, a group can be excluded from power, and thus be a *Powerless* or *Discriminated* group, depending on whether there is explicit active discrimination against it or not. Importantly, whenever political changes occurred in the same year as a conflict, the coding purposely reflects the power relations *before* the outbreak of the violence, to avoid endogeneity issues.

Importantly, the EPR dataset can also be linked to the Uppsala Conflict Data Program (UCDP) Actor Dataset (2014). In this way it is possible to know whether any rebel group that is included in the UCDP dataset and that has been involved in a civil conflict against the central state can be associated to a specific ethnic group. Ethnic groups ruling alone can never appear involved in any ethnic conflict according to this definition, as they can never fight the central state, which is under their sole control.

[3]In the GeoEPR dataset ethnicity is defined as "*a subjectively experienced sense of commonality based on a belief in common ancestry and shared culture*". Politically relevant ethnic groups are those that either have at least one significant political actor claiming to represent their interests in the national political arena or are systematically and intentionally discriminated against in the domain of public politics (Girardin et al., 2015).

Rainfall & Growing season For our analysis, we rely on the ERA-40 dataset, which contains rainfall data provided by the European Centre for Medium-Term Weather Forecasting (ECMWF).[4] The dataset provides re-analysis of weather data, obtained through a climatic model (called IFS CY23r4) that harmonizes information from a variety of primary sources, which include weather stations, ships, aircraft, weather balloons, radiosondes, and satellites orbiting the earth (for more details, see Kållberg et al., 2004). This appears to be one of the best available sources for African weather data, especially given the low quality of rainfall gauge data that are available for this region.[5] The ERA-40 dataset provides rainfall information at six-hour frequency from 1958 until 2001 and at a 1.25 degree resolution (corresponding to about 140 square kilometers at the equator). While some noise in rainfall data is unavoidable, precision is expected to be significantly better once global satellite data became available, in the late seventies – right before the beginning of our study period. Moreover, the fact that data are provided in a spatially aggregated format (at 1.25 degree resolution), and that we will temporally aggregate them to construct our measures of interest, helps partially attenuating the noise in the rough data.

To construct rainfall during the *growing season*, we follow a similar approach as Kudamatsu et al. (2014). The main input is provided by the Normalized Difference Vegetation Index (NDVI) dataset (Tucker et al., 2005), which contains bi-weekly measures of plant growth since January 1982, with a resolution of 8×8 km. More specifically, the NDVI dataset is generated using satellite images that record red and infra-red radiances and reflectances, which are highly correlated with photosynthetically active biomass, chlorophyll abundance, and energy absorption, and which therefore allow estimating plant growth on the hearth surface. We use TIMESAT – a software developed by Jönsson and Eklundh, two Swedish ecologists – to remove the noise from the NDVI data, due for instance to cloud cover. The program uses an adaptive Savitzky-Golay filtering method as well as methods based on upper envelope weighted fits to asymmetric Gaussian and double logistic model functions. From the fitted model functions a number of phenological parameters can be extracted, including the beginning and end of the growing season, which are defined as the time period in between 20% above one trough of the smoothed NDVI index to 20% above the next trough (see Jönsson and Eklundh (2004) for more details). This allows us to determine the growing season within each 8×8 km NDVI pixel. Given that year-specific variations in the growing season are endogenous to weather conditions (as farmers likely adapt their behavior according to the weather), we average start and end dates over the study period for each pixel.[6] Figures A.1 to A.3 illustrate the distribution of the average beginning, end and length of the growing season in the region of interest for our study. For the analysis, we then aggregate that fine-gridded measure at the 1.25×1.25 degrees grid resolution to obtain the average growing season within each rainfall grid-cell. The yearly rainfall during the growing season for each ethnic group and each country is then obtained by overlaying the grids with the spatial

[4]The dataset can be downloaded from `http://apps.ecmwf.int/datasets/data/era40-daily/` (Accessed: November 2015).

[5]See Kudamatsu et al. (2014) for a discussion of the advantages of this source over alternatives.

[6]Whenever more than one growing season is identified (which happens in 8.1% of the cases), we follow Kudamatsu et al. (2014) and focus on the first growing season of the year. 3.8% of the observations have no growing season, while 7.5% have a 12-months growing season.

ethnicity and administrative maps, as reported in Figures 1 and B.2, in the main text.

A.2. Additional Controls

Agricultural Output Our measures of agricultural production are taken from FAO, which records information on four key aggregates: cereals, crops, agriculture and food.[7] Estimates are based on information collected from governments as well as from national and international agencies and organizations.[8] For our analysis we consider gross production indexes, which record, for each category, the aggregate volume of production for each year relative to the base period 2004-2006. More specifically, production quantities of each commodity are weighted by 2004-2006 average international commodity prices and summed for each year; the aggregate for a given year is then divided by the average aggregate for the base period 2004-2006, to obtain the final index.

Nightlight Data on nightlight density is provided by the National Geophysical Data Center (NGDC) on a yearly basis, starting from 1992. Several satellites of the US Air Force circle around the earth 14 times a day observing every location on the planet at some instant between 8 and 10 pm local time. Each satellite dataset consists of a grid which reports the average yearly light density with a six-bit digital number (an integer between 0 and 62).[9] The grid comes at a very high resolution, equal to approximately 0.86 square kilometers at the equator. We first compute average nightlight density for each of our 1.25 $\times$ 1.25 degree cells (defined by the rainfall data) and then compute nightlight density inequality measures in exactly the same way as the rainfall inequality measures. Following Alesina et al. (2014), we weight nightlight density in each grid by the population of that area, using data from the Gridded Population of the World.[10]

[7]Production records for these four aggregates include the quantities of the commodities sold in the market (i.e. marketed production) and the quantities consumed or used by the producers (i.e. auto-consumption). Moreover, when calculating production indexes for agriculture and food, all intermediate primary inputs of agricultural origin are deducted. Finally, the category of food production includes all commodities that are considered edible and that contain nutrients, including commodities derived as a result of further processing.

[8]Governments have supplied most of the information in the form of replies to annual FAO questionnaires. Use has also been made of information supplied by other national or international agencies or organizations. According to FAOstat, to make the coverage as complete as possible, in some cases official governmental data are supplemented with data from unofficial sources.

[9]The nightlights data can be downloaded from `http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html` (Accessed: November 2015). There are two different datasets that can be downloaded for each year: *Average Visible, Stable Lights, & Cloud Free Coverages* and *Average Lights $\times$ Pct*, the main difference being that the latter multiplies lights by the percent frequency of light detection and is mostly used to infer gas flaring volumes. Moreover, for some years two observations are available, as data were collected from two different satellites. We rely on the *Average Visible, Stable Lights, & Cloud Free Coverages* dataset and for years that have two observations we consider an average of the two.

[10]The data is based on censuses and other population surveys at various levels and can be downloaded from: `http://sedac.ciesin.columbia.edu/data/collection/gpw-v3` (Accessed: November 2015). The dataset estimates human population for the years 1990, 1995, and 2000 by 30 arc-second (about 1km) grid cells. Values are linearly interpolated and extrapolated for the missing years.

Temperature Information on temperature is provided by ECMWF with the same frequency and format as information on rainfall. The construction of the temperature-based inequality measure closely mirrors the construction of the rainfall-based measures.

Malaria Prevalence In order to construct the index for malaria risk we follow Kudamatsu et al. (2014). The index is based on a combination of four temperature and rainfall conditions that determine the ability of malaria parasites and vector to survive and regenerate. More specifically, we use monthly rainfall and temperature measures aggregated by grid-cell to generate a monthly indicator variable that takes on the value of 1 when the following four conditions are met: 1) average monthly rainfall in the previous 3 months is at least 60mm; 2) rainfall in at least one of these months is above 80 mm; 3) no month in the previous 12 has an average temperature below 5 C; 4) The average temperature in the previous 3 months exceeds the sum of 19.5 C and the standard-deviation of monthly average temperature in the past 12 months (see Kudamatsu et al. (2014) for more details). For each grid-cell we then compute the share of months within a year in which the malaria-prevalence index takes on the value of 1. Finally, we take the weighted average of this measure across all grids covering a country in order to obtain a country-specific measure of malaria prevalence.[11]

Transportation Costs We construct a measure of rainfall-induced transport costs, by relying on the digitalized map of the road system provided by the Global Roads Open Access Data Set (gROADS). Due to variations in the original sources that are combined to create the dataset, the road network refers to different years for different countries, ranging from the 1980s to 2010. To the best of our knowledge, there is no database systematically recording the evolution of the road system through Africa over time and we therefore rely on the gROADS data as the best available proxy for the period under consideration. To generate our variable of interest we first create a 10-meter buffer around each road and then compute the yearly amount of rainfall over each buffer. We finally weight the road rainfall by each roads relative length to obtain the country-wide average.

Other Controls In the robustness check section, we also consider a set of additional variables that have been found to affect conflict prevalence. While acknowledging that some of these variables are likely to be endogenous to conflict itself, we will show that our findings remain robust to their inclusion. Data on *population*, *GDP per capita* (at 2005 constant prices) and *openness to trade* are taken from Penn World Table 7.1 (Henston et al., 2012). Data on *institutional quality* is taken from the Polity IV database, provided by the Center for Systemic Peace.[12] Figures on *aid inflows*, recorded as gross disbursement in constant

[11] Once again, weights refer to the share of the country covered by each grid-cell and account for the fact that some cells do not fall completely within the country borders.

[12] The standard polity IV index is constructed combining two comprehensive variables: 1) the democracy indicator, which is an additive eleven-point scale (0-10) variable derived from coding of the competitiveness of political participation, the openness and competitiveness of executive recruitment and constraints on the chief executive. 2) the autocracy indicator, which is another additive eleven-point scale (0-10) variable derived from coding of the competitiveness of political participation, the regulation of participation, the openness and competitiveness of executive and constraints on the chief executive. The final index is

USD dollars, is taken from the Creditor Reporting System database kept by the OECD.[13] Information on *natural disasters* is taken from the Emergency Events Database (EM-DAT) kept by the Centre for Research on the Epidemiology of Disasters (CRED).[14] Finally, information on the geographic location and discovery date of *oil and gas fields* is taken from the PETRODATA dataset, provided by Lujala et al. (2007).[15]

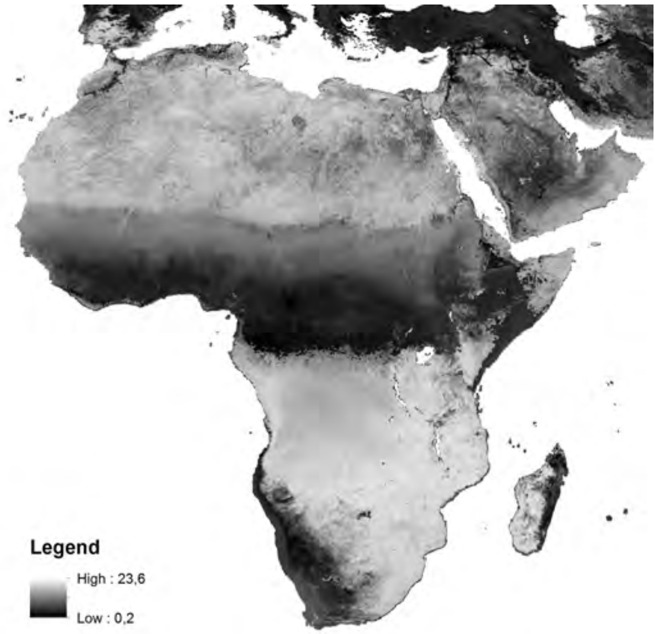
computed by subtracting the autocracy score from the democracy score; the resulting unified polity scale ranges therefore from +10 (strongly democratic) to -10 (strongly autocratic). See Marshall et al. (2013) for further details.

[13]The database records worldwide flows in Official Development Assistance (ODA) since 1973, disaggregated by donor, recipient and purpose. In order to construct our variable we aggregate all flows received by each country in a given year. ODA is defined as *"those flows to developing countries and multilateral institutions provided by official agencies, including state and local governments, or by their executive agencies, each transaction of which meets the following tests: i) it is administered with the promotion of the economic development and welfare of developing countries as its main objective; and ii) it is concessional in character and conveys a grant element of at least 25 per cent."*

[14]The EM-DAT dataset records all natural disasters since 1900 that fulfill at least one of these four criteria: 1) ten or more people reported killed; 2) hundred or more people reported affected; 3) declaration of a state of emergency; 4) call for international assistance. For each disaster the database combines information from different sources, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies, and reports, among other things, the number of people that died, the number of people affected and the estimated total damages. We define our variable as the total number of individuals affected by the natural disaster, obtained by summing up the number of individuals that died (which includes missing individuals), got injured, lost their house and/or required basic survival needs (such as food, water, shelter, sanitation or immediate medical assistance) as a consequence of the disaster.

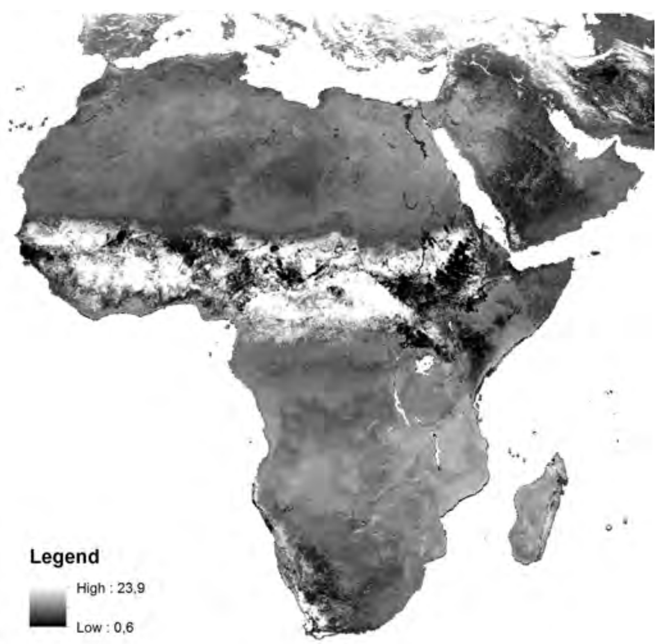
[15]Two different datasets are available for onshore and offshore fields. For our analysis, we focus on onshore fields. Data as well as explanatory material can be found at `https://www.prio.org/Data/Geographical-and-Resource-Datasets/Petroleum-Dataset/Petroleum-Dataset-v-12/` (Accessed: November 2015).

Figure A.1: Growing Season Start



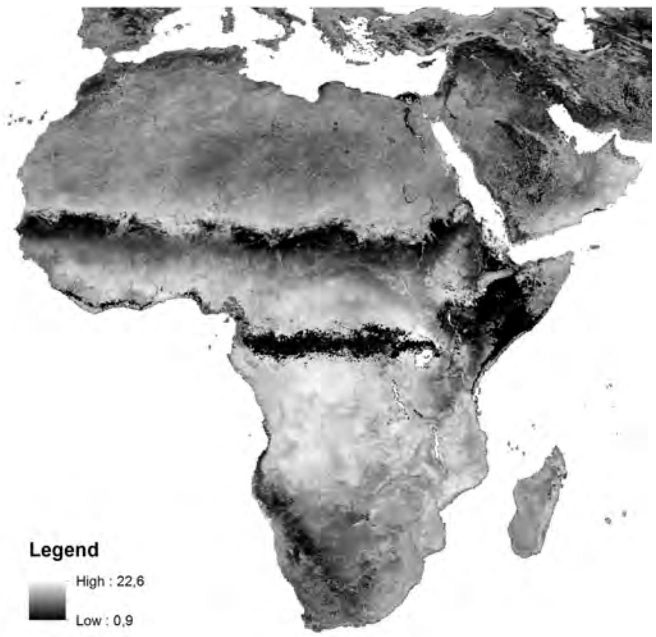
Notes: The figure shows the estimated start of the growing season for each 8 × 8 km pixel. Start dates range from 0 to 24 because the year has been devided in bi-weekly intervals, corresponding to the frequency with which satellite images are captured.

Figure A.2: Growing Season End



Notes: The figure shows the estimated end of the growing season for each 8 × 8 km pixel. End dates range from 0 to 24 because the year has been devided in bi-weekly intervals, corresponding to the frequency with which satellite images are captured.

Figure A.3: Growing Season Length



Notes: The figure shows the estimated length of the growing season for each 8×8 km pixel. Lenght ranges from 0 to 24 because the year has been devided in bi-weekly intervals, corresponding to the frequency with which satellite images are captured.

Appendix B – Extra Figures

Figure B.1: Number of years of civil conflict by country

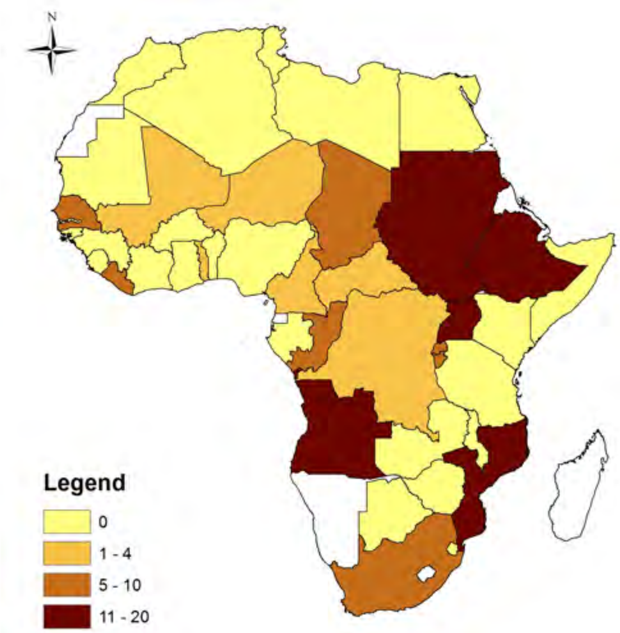


Fig. B.1a: Ethnic Conflicts

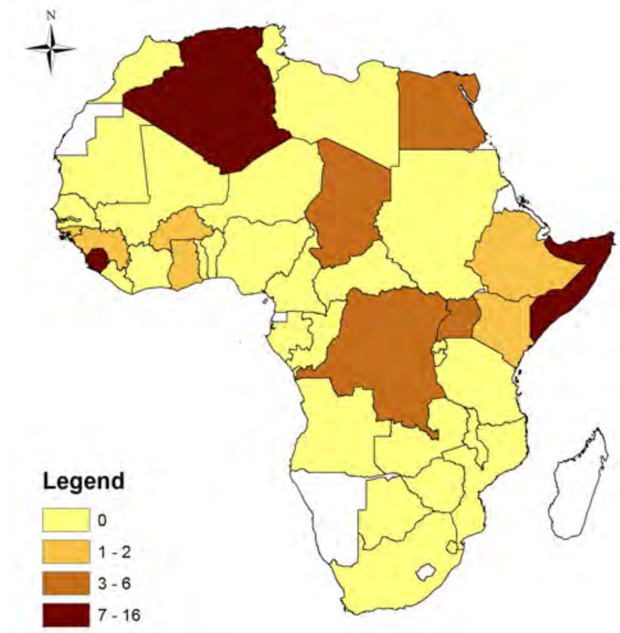
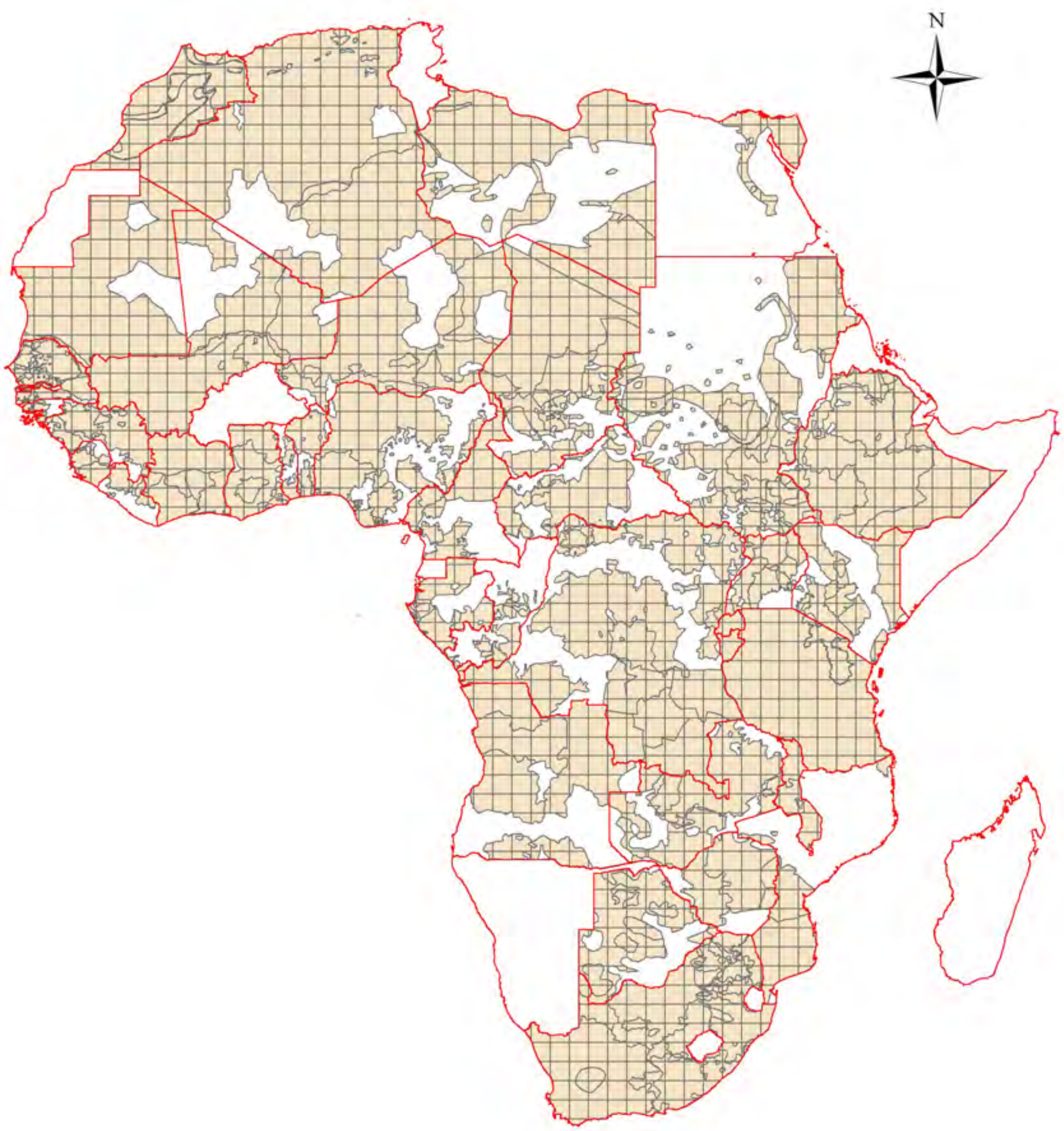


Fig. B.1b: Non-Ethnic Conflicts

Notes: The two figures illustrate the number of years in which a country was involved in ethnic (Figure 1a) or non-ethnic (Figure 1b) civil conflicts, over the period 1982-2001. The classification of civil conflicts is taken from the Ethnic Armed Conflict (EAC) dataset provided by Wimmer et al. (2009), which builds on the PRIO/Uppsala civil conflict database (Gleditsch et al., 2002). Different colors indicate different quartiles. Areas in white are excluded from the analysis.

Figure B.2: Dataset construction – GeoEPR



Notes: The figure shows how the dataset has been constructed, by spatially merging three different data sources: the ECMWF rainfall grid of 1.25 $\times$ 1.25 degree cells, the yearly Georeferenced EPR (GeoEPR) maps of ethnic boundaries from 1982 until 2001 (gray lines), and an administrative map of Africa (red lines). Areas in white are excluded from the analysis: Lesotho and Madagascar are excluded because they only host one ethnic homeland; Eritrea and Namibia are excluded because the two countries only became independent during the period under consideration; Zambia is excluded because it has multiple groups simultaneously recorded as *Senior Partners*; other white areas indicate that no politically relevant ethnic group was recorded there.

Figure B.3: Average and Standard-Deviation in BGRI

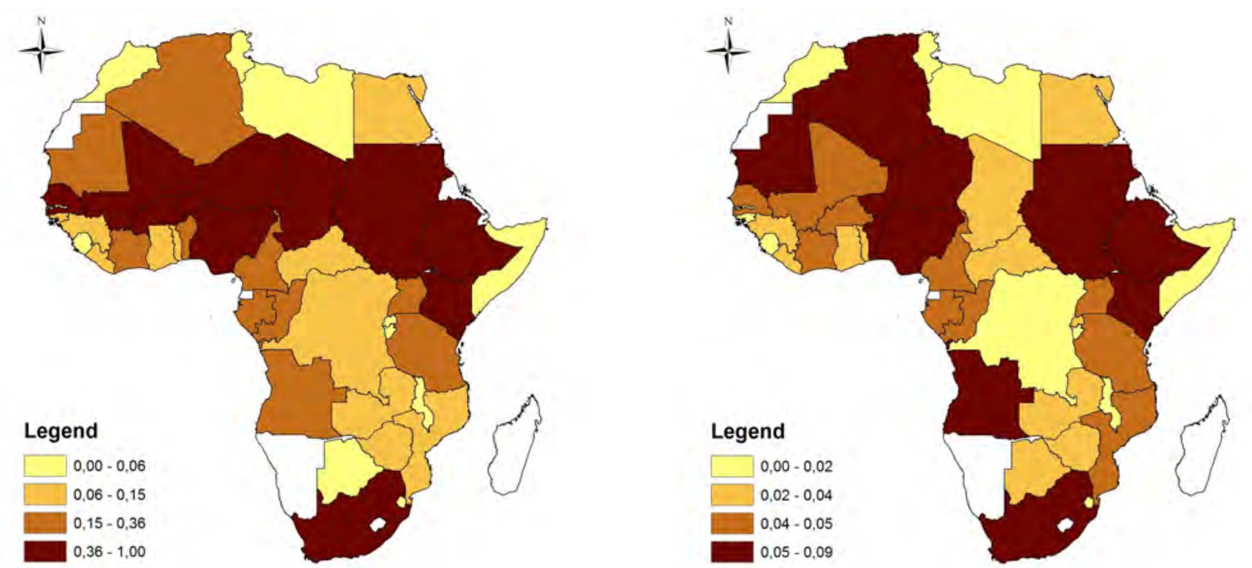
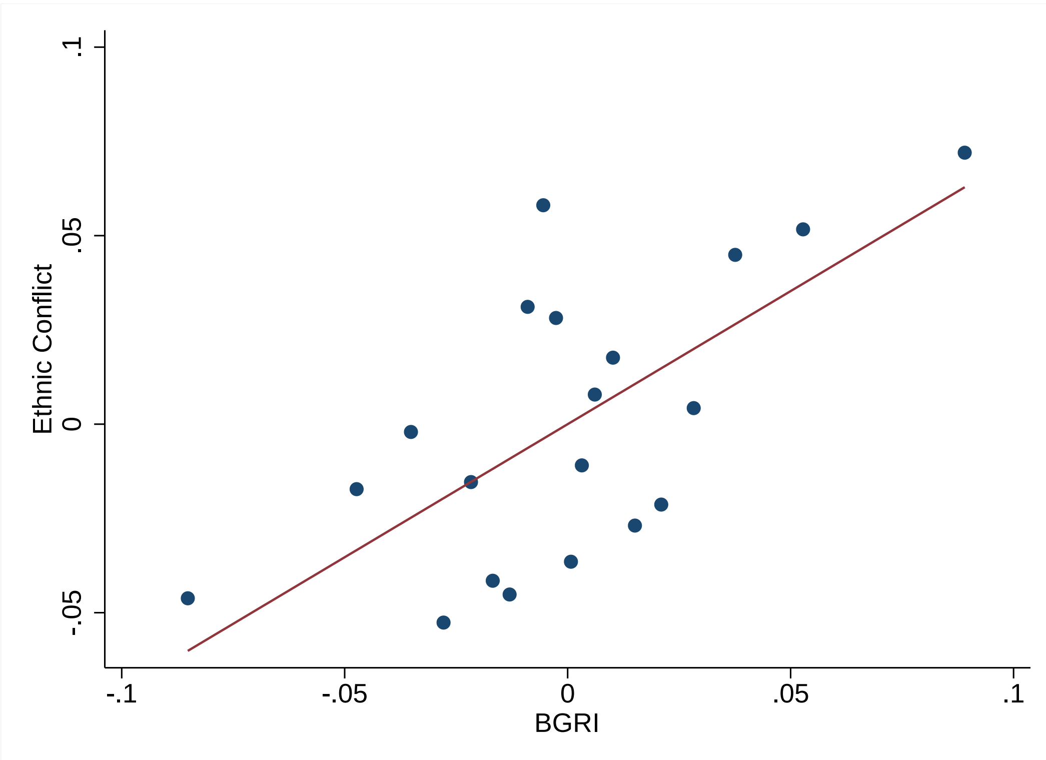


Fig. B.3a: BGRI Average

Fig. B.3b: BGRI Standard-Deviation

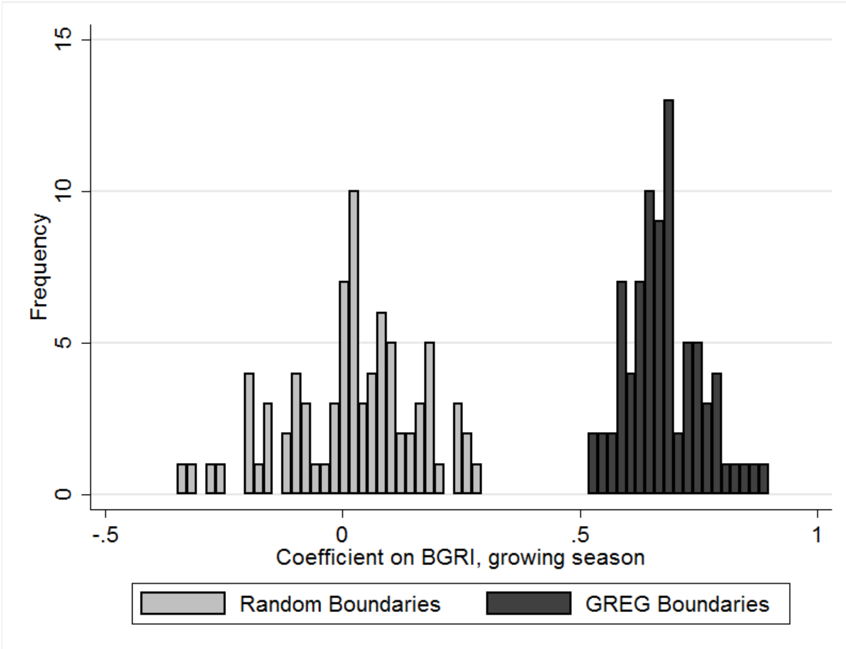
Notes: The figures illustrate the average (Figure B.1a) and standard-deviation (Figure B.1b) of Between-Group Rainfall Inequality (BGRI) over the period 1982-2001, by country. Different colors indicate different quartiles. Areas in white are excluded from the analysis.

Figure B.4: BGRI and Ethnic Conflict



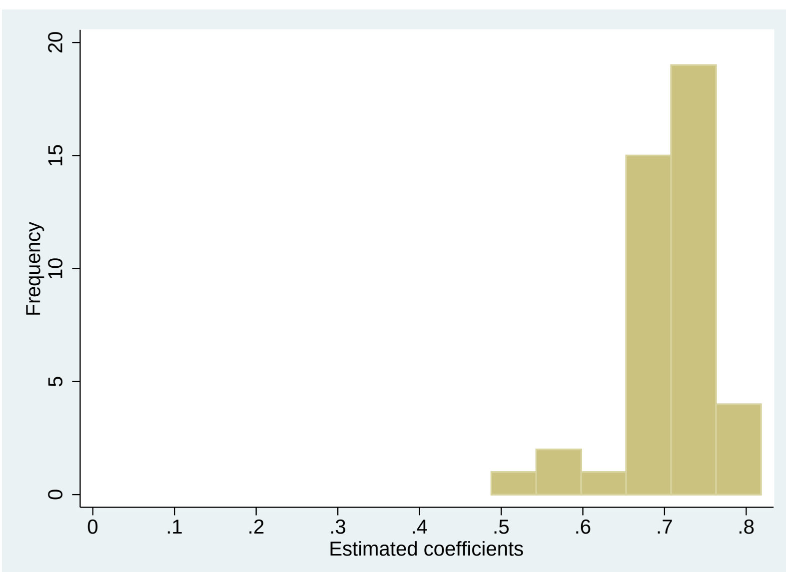
Notes: The graph illustrates non-parametrically the relationship between Ethnic Conflict and Between-Group Rainfall Inequality (BGRI). Values on the Y axes and X are residuals from regressions including country fixed effects, year fixed effects, and country-specific time trends. Dots indicates average across equal-size bins. A linear regression line based on the ungrouped data is also shown.

Figure B.5: Placebo test



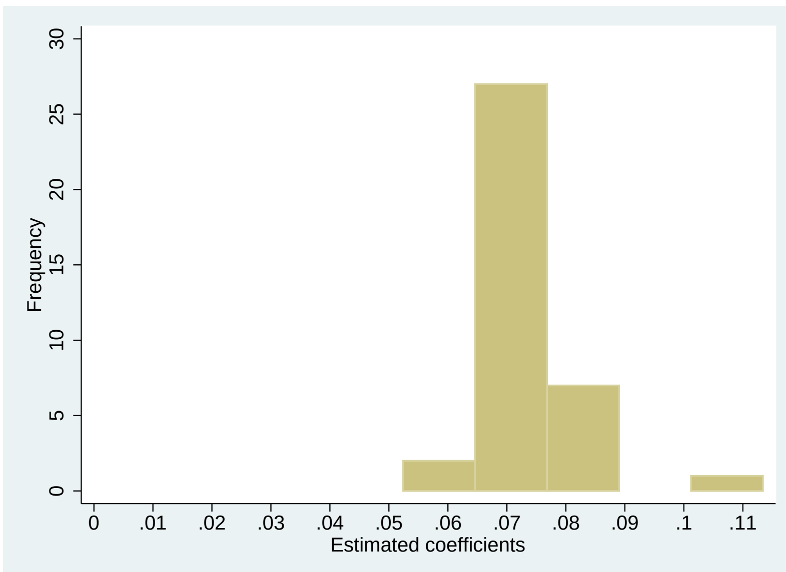
Notes: The figure reports the distribution of the coefficients of our original BGRI measure (in dark color) and of an alternative BGRI measure constructed by randomly redrawing the African ethnic boundaries, fixing the original area distribution (in light color). The random re-drawing was repeated a 100 times and each time we run a regression based on our main specification, in which included both the original and the newly constructed "placebo" measures.

Figure B.6: BGRI estimates with different samples



Notes: The figure reports the coefficients on Between-Group Rainfall Inequality BGRI when dropping one country at a time. The estimate is based on the main specification reported in column 2 of Table 2.

Figure B.7: RI_i^{power-} estimates with different samples



Notes: The figure reports the coefficients on Rainfall Inequality RI_i^{power-} when dropping one country at a time. The estimate is based on the specification reported in column 4 in Table 8.

Appendix C – Additional Tables

Table C.1: List of Countries – GREG

	Total Years	Years of Ethnic Conflict	Years of Non-Ethnic Conflict	# of Ethnic Groups
ALGERIA	20	0	11	8
ANGOLA	20	20	0	13
BENIN	20	0	0	9
BOTSWANA	20	0	0	6
BURKINA FASO	20	0	1	15
BURUNDI	20	10	0	2
CAMEROON	20	1	0	20
CENTRAL AFRICAN REPUBLIC	20	1	0	11
CHAD	20	7	3	17
CONGO	20	5	0	10
CôTE D'IVOIRE	20	0	0	12
DEMOCRATIC REPUBLIC OF THE CONGO	20	2	4	31
EGYPT	20	0	6	4
ETHIOPIA	20	15	1	17
GABON	20	0	0	7
GAMBIA	20	0	0	3
GHANA	20	0	1	12
GUINEA	20	0	2	10
GUINEA-BISSAU	20	0	2	9
KENYA	20	0	1	16
LIBERIA	20	9	0	9
LIBYA	20	0	0	4
MALAWI	20	0	0	5
MALI	20	2	0	10
MAURITANIA	20	0	0	4
MOROCCO	20	0	0	6
MOZAMBIQUE	20	11	0	9
NIGER	20	4	0	11
NIGERIA	20	0	0	27
RWANDA	20	10	0	2
SENEGAL	20	9	0	11
SIERRA LEONE	20	0	10	6
SOMALIA	20	0	16	4
SOUTH AFRICA	20	7	0	13
SUDAN	20	19	0	30
SWAZILAND	20	0	0	3
TANZANIA	20	0	0	30
TOGO	20	2	0	11
TUNISIA	20	0	0	4
UGANDA	20	14	4	14
ZAMBIA	20	0	0	11
ZIMBABWE	20	0	0	10

Notes: The table lists all countries included in the sample, which covers the period 1982-2001. For each country, the table indicates the number of years (within the study period) in which the country experienced a *civil* conflict – defined as an armed conflict between the government of the state and one or more internal opposition group(s) that caused at least 25 battle-related deaths within that year. The table distinguishes between ethnic and non-ethnic civil conflicts. The list of civil conflicts is taken from the PRIO/Uppsala armed conflict database (Gleditsch et al., 2002), while the classification in ethnic or non-ethnic conflict is based on the Ethnic Armed Conflict (EAC) dataset provided by Wimmer et al. (2009). The number of ethnic groups whose boundaries are located within each country is taken from the GREG map. More details on the different sources and definitions are reported in the main text.

Table C.2: List of countries – GeoEPR

	Total Years	Years of Ethnic Conflict	Years of Non-Ethnic Conflict	# of Ethnic Groups
ALGERIA	20	0	11	2
ANGOLA	20	20	0	5
BENIN	20	0	0	4
BOTSWANA	20	0	0	7
BURUNDI	20	10	0	2
CAMEROON	20	1	0	6
CENTRAL AFRICAN REPUBLIC	20	1	0	4
CHAD	20	7	3	6
CONGO	20	5	0	6
CôTE D'IVOIRE	20	0	0	5
DEMOCRATIC REPUBLIC OF THE CONGO	20	2	4	13
EGYPT	20	0	6	2
ETHIOPIA	20	15	1	9
GABON	20	0	0	5
GAMBIA	12	0	0	4
GHANA	20	0	1	5
GUINEA	20	0	2	3
GUINEA-BISSAU	20	0	2	3
KENYA	20	0	1	8
LIBERIA	13	3	0	5
LIBYA	20	0	0	4
MALAWI	20	0	0	3
MALI	20	2	0	3
MAURITANIA	20	0	0	4
MOROCCO	20	0	0	3
MOZAMBIQUE	20	11	0	3
NIGER	19	3	0	5
NIGERIA	20	0	0	6
RWANDA	20	10	0	2
SENEGAL	20	9	0	5
SIERRA LEONE	12	0	3	4
SOUTH AFRICA	20	7	0	12
SUDAN	20	19	0	15
TANZANIA	20	0	0	4
TOGO	20	2	0	2
UGANDA	16	14	0	8
ZIMBABWE	10	0	0	4

Notes: The table is similar to Table C.1 and lists all countries included in the analysis based on the dynamic GeoEPR sample. For each country, the table indicates the number of years (within the study period) in which the country experienced a *civil* conflict – defined as an armed conflict between the government of the state and one or more internal opposition group(s) that caused at least 25 battle-related deaths within that year. The table distinguishes between ethnic and non-ethnic civil conflicts. The list of civil conflicts is taken from the PRIO/Uppsala armed conflict database (Gleditsch et al., 2002), while the classification in ethnic or non-ethnic conflict is based on the Ethnic Armed Conflict (EAC) dataset provided by Wimmer et al. (2009). The number of ethnic groups whose boundaries are located within each country is taken from the dynamic GeoEPR map. The dataset covers the period 1982-2001. Excluded years for some countries are due to the fact that: 1) no ethnic group is recorded in the GeoEPR map (Uganda and Zimbabwe); 2) the state is recorded as *collapsed* (Sierra Leone and Liberia); 3) there is no *leading* ethnic group recorded (Gambia); 4) there are multiple *Senior Partners* recorded in the same year (Niger).

Table C.3: Rainfall inequality measures – Correlation matrix

	BGRI, growing	BGRI, non-growing	WGRI, growing	NRI, growing	BGNI	BGRI, growing, Adm units	BGRI, growing, SDs	BGI, growing, temperature	BGRI, growing, EPR	$BGRI^{power}$, growing	$BGRI^{size}$, growing
BGRI, growing season	1.00										
BGRI, non-growing season	0.44	1.00									
WGRI, growing season	−0.13	−0.43	1.00								
NRI, growing season	0.71	0.08	0.60	1.00							
BGNI	0.51	0.63	−0.47	0.07	1.00						
BGRI, growing season, adm units	0.73	0.11	0.56	0.98	0.09	1.00					
BGRI, growing season, SDs	0.35	0.54	−0.45	−0.01	0.64	−0.00	1.00				
BGI, growing season, temperature	0.50	0.35	−0.15	0.36	0.33	0.28	0.42	1.00			
BGRI, growing season (EPR)	0.89	0.30	−0.00	0.70	0.32	0.74	0.17	0.41	1.00		
$BGRI^{power}$, growing season	0.67	0.23	0.11	0.59	0.22	0.63	0.06	0.17	0.70	1.00	
$BGRI^{size}$, growing season	0.73	0.25	0.08	0.62	0.26	0.68	0.09	0.24	0.84	0.82	1.00

Notes: The table shows pairwise correlation across all the country-wide inequality measures used in the analysis. **BGRI** indicates Between-Group Rainfall Inequality. **WGRI** indicates Within-Groups Rainfall Inequality. **NRI** indicates National Rainfall Inequality. **BGNI** measures Between-Group Nightlight Inequality. ***Adm units*** indicates that the inequality measure was computed considering level 1 administrative borders rather than ethnic homeland's boundaries. ***SDs*** indicates that the inequality measure was computed comparing yearly deviations from each ethnic-group average rainfall, instead than comparing rainfall levels. ***Temperature*** indicates that the inequality measure refers to inequality in temperature, rather than in rainfall. ***EPR*** indicates that the measure is based on the GeoEPR dataset. $\mathbf{BGRI}^{power}$ indicates that the inequality measure is constructed with respect to the rainfall received by the *leading* ethnic group – meaning the ethnic group that is classified in the EPR dataset as *Monopolist*, *Dominant* or *Senior Partner*. $\mathbf{BGRI}^{size}$ indicates that the inequality measure is constructed with respect to the rainfall received by the ethnic group with the largest population.

Table C.4: Alternative specifications

Dependent Variable:	Ethnic Conflict						
Reference Table:	Table 2		Table 6	Table D.2			
Reference Regression in the Table:	3		6	4	8	4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BGRI, growing season	0.676*	0.746*	0.650**	0.644*	0.573*	0.678*	0.678*
	(0.331)	(0.368)	(0.292)	(0.337)	(0.275)	(0.331)	(0.337)
BGRI, growing season (t-1)	0.493*	0.540*		0.490*	0.303	0.499*	0.524*
	(0.270)	(0.285)		(0.269)	(0.198)	(0.264)	(0.271)
BGRI, growing season (t-2)		0.483					
		(0.373)					
Ethnic Conflict (t-1)			0.245*		0.338**		
			(0.140)		(0.128)		
Rainfall growth, growing season				−0.035	0.013		
				(0.036)	(0.059)		
Rainfall growth, growing season (t-1)				−0.029	−0.054		
				(0.032)	(0.034)		
Rainfall, growing season						0.001	
						(0.002)	
Rainfall, growing season (t-1)						0.001	
						(0.002)	
Rainfall SD, growing season							0.002
							(0.014)
Rainfall SD, growing season (t-1)							0.014
							(0.011)
Controls	no	no	no	no	yes	no	no
Neighbors Controls	no	no	no	no	yes	no	no
Lagged Controls	no	no	no	no	yes	no	no
Country Effects	yes	yes	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes	yes	yes
Country Time Trends	yes	yes	yes	yes	yes	yes	yes
R^2	0.70	0.70	0.73	0.70	0.75	0.70	0.70
Years	19	18	20	19	20	19	19
Countries	42	42	42	42	42	42	42
N	798	756	840	798	835	798	798

Note: All inequality measures have been normalized by taking $(X - X_{min})/(X_{max} - X_{min})$. Both regression 1 and regression 2 replicate regression 3, from Table 2, when, respectively, the first (i.e. 1982) and first two (i.e. 1982 - 1983) years in the sample are excluded. Regression 3 replicates regression 6, from Table 6, when a GMM estimator is used, instrumenting the first lag of the dependent variable with its second lag. Regression 4 and regression 5 replicate, respectively, regressions 4 and 8, from Table D.2, when the first year in the sample (i.e. 1982) is excluded. Regression 6 and regression 7 replicate (again) regression 4, from Table D.2, when the first year in the sample (i.e. 1982) is excluded and the rainfall growth measure is replaced with, respectively, a country-wide measure of average rainfall, or the deviation from the average rainfall level over the sample period (expressed in Standard-Deviation units). Two-way clustered standard errors by year and country in parentheses, adjusted for low number of clusters, using the number of years. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.5: Alternative polarization and fractionalization measures

Dependent Variable:	Ethnic Conflict									
	Fract	PREG	ELF	Alesina	Fearon	Roeder	S&M	BAH	ETHPOL	ETHFR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BGRI, growing season	0.932**	1.265***	1.481***	1.238***	1.236***	1.433***	1.148***	1.358***	0.981***	1.079**
	(0.401)	(0.305)	(0.425)	(0.389)	(0.376)	(0.446)	(0.352)	(0.410)	(0.321)	(0.402)
NRI, growing season	−0.144	−0.563	−0.106	−0.316	−0.332	−0.046	−1.008**	−0.242	−0.349	−0.110
	(0.166)	(0.376)	(0.298)	(0.709)	(0.663)	(0.361)	(0.406)	(0.323)	(0.690)	(0.353)
NRI × Index	−0.205	0.096	−1.011	−0.291	−0.265	−0.976	1.181	−0.530	0.256	−0.304
	(0.811)	(1.024)	(0.781)	(1.278)	(1.142)	(0.948)	(0.959)	(0.837)	(1.422)	(0.942)
Country Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country Time Trends	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.70	0.69	0.70	0.70	0.70	0.70	0.69	0.70	0.70	0.70
Years	20	20	20	20	20	20	20	20	20	20
Countries	42	36	37	37	37	37	36	36	39	39
N	840	720	740	740	740	740	720	720	780	780

Note: All inequality measures have been normalized by taking $(X - X_{min})/(X_{max} - X_{min})$. Regression 1 considers a *Fractionalization* Index constructed for each country as $1 - (\sum_{i=1}^{E} n_i^2)$ where n is the relative size of ethnic group i. Regressions 2 to 10 rely on the following indexes: Politically Relevant Ethnic Groups from Posner (2004); ethnolinguistic fractionalization from the *Soviet Atlas Narodov Mira*; ethnic fractionalization from Alesina, Devleeschauwer, Easterly, Kurlat, and Wacziarg (2003); ethnic fractionalization from Fearon (2003); ethnic fractionalization index from Roeder (2001, based on 1961 data); ethnic fractionalization from Scarritt and Mozaffar (1999); ethnic fractionalization from Morrison et al. (1989); ethnic polarization from Montalvo and Reynal-Querol (2005); ethnic fractionalization from Montalvo and Reynal-Querol (2005). Values for the indexes used in columns 2 to 8 are taken from Table 1 in Posner (2004), while values for the indexes in columns 9 and 10 are taken from the Appendix B in Montalvo and Reynal-Querol (2005). We invite the reader to consult the original sources for more details and references on each specific index. Two-way clustered standard errors by year and country in parentheses, adjusted for low number of clusters, using the number of years. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.6: Ethnic Power Relations – Alternative specifications

Dependent Variable:	Rebel grup fighting in the name of the ethnic group								
"Downgraded" Specification:	*n.a.*			*By 1 step*	*To no power*	*In 5 years*	*n.a.*	*By 1 step*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RI^{power-}, growing season	0.092*	0.076**	0.032**	0.062**	0.062**	0.050	0.083**	0.064**	0.046
	(0.044)	(0.034)	(0.014)	(0.024)	(0.023)	(0.034)	(0.033)	(0.027)	(0.027)
RI^{power+}, growing season	0.002	0.010	−0.005	0.011	0.011	0.010			
	(0.006)	(0.010)	(0.027)	(0.011)	(0.011)	(0.011)			
Oil share	0.153*								
	(0.073)								
$I(r^{LEAD}>2SD)$		−0.028							
		(0.020)							
Downgraded × RI^{power-}				0.250***	0.294***	0.081***		0.259***	0.334***
				(0.059)	(0.086)	(0.025)		(0.062)	(0.086)
Downgraded × RI^{power+}				−0.002	0.011	0.027		0.024	−0.019
				(0.049)	(0.090)	(0.035)		(0.074)	(0.050)
Downgrade				0.010	0.044	0.030		0.005	−0.038
				(0.057)	(0.112)	(0.045)		(0.058)	(0.039)
RI^{power-} × RainfallSD							0.015	0.004	
							(0.010)	(0.012)	
RainfallSD							−0.005	−0.003	
							(0.006)	(0.007)	
Downgraded × RI^{power-} × RainfallSD								0.030	
								(0.050)	
Downgraded × RI^{power-} × $I(Rain< \bar{r}_i)$									−0.116
									(0.120)
$I(Rain< \bar{r}_i)$									0.001
									(0.009)
RI^{power-} × $I(Rain< \bar{r}_i)$									0.019**
									(0.007)
Hidden Interactions	no	no	no	no	no	no	no	yes	yes
Ethnicity Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country Time Trends	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.70	0.70	0.45	0.71	0.71	0.70	0.70	0.71	0.71
Ethnicities	80	172	178	172	172	172	172	172	172
Countries	16	37	37	37	37	37	37	37	37
N	1545	2995	5663	2995	2995	2995	2995	2995	2995

Note: This table builds on Table 8 in the main text. Summary statistics for the new variables used in this table are reported in Table C.7. **Oil Share** indicates the share of the country's surface covered with oil and gas that falls within the ethnic group's territory. **I(r^{LEAD}>2SD)** is an indicator variable that takes on the value of 1 when the leading ethnic group in the country receives an amount of rainfall more than 2SD above the average level it received over the period 1982-2001. **Downgraded** is an indicator variable that takes on the value of 1 whenever the ethnic group was downgraded in the power scale provided in the EPR dataset. The variable used in regressions 4, 8, and 9 captures whether the group was downgraded during the previous year. The variable used in regression 5 takes captures whether the group was downgraded from having at least some power (i.e. *Junior Partner* or above) to having no power (i.e. *Powerless* or below). The variable used in regression 6 captures whether the group was downgraded at any point during the previous 5 years. **I(Rain**$< \bar{r}_i$**)** is an indicator variable that takes on value of 1 when the ethnicity receives less rainfall than its average over the period 1982-2001. Regressions in column 8 and 9 include also triple interaction with RI^{power+} as well as all double interactions. Due to space constraints, they are not reported, but none of the hidden coefficients is statistically significant. The main sample includes 172 ethnic groups, 37 countries, and 20 years (1982-2001). Column 3 extends the sample to include the period 1960-2001. Two-way clustered standard errors by year and country in parentheses, adjusted for low number of clusters (with the exception of results reported in column 3), using the number of years. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.7: Summary Statistics – Additional variables

	Mean	Min	Max	Std.dev.	Obs
Oil share	0.16	0.00	1.00	0.29	1545
Downgraded, t-1	0.02	0.00	1.00	0.13	2995
Downgraded to no power, t-1	0.01	0.00	1.00	0.10	2995
Downgraded, t-5	0.08	0.00	1.00	0.27	2995
I(r^{LEAD}>2SD)	0.03	0.00	1.00	0.16	2995
I(Rain$< \bar{r}_i$)	0.61	0.00	1.00	0.49	2995

Notes: The variables reported in this table refer to analysis based on the EPR sample. **Oil Share** is constructed following Morelli and Rohner (2015) and indicates the share of the country's surface covered with oil and gas that falls within the ethnic group's territory. **Downgraded, t-1** is an indicator variable that takes on the value of 1 when the ethnic group was downgraded in the power scale provided in the EPR dataset, during the previous year. **Downgraded to no power, t-1** takes on the value of 1 only if the group was downgraded from having at least some power (i.e. *Junior Partner* or above) to having no power (i.e. *Powerless* or below). **Downgraded, t-5** takes on the value of 1 if the group was downgraded at any point during the previous 5 years. **I(r^{LEAD}>2SD)** is an indicator variable that takes on the value of 1 when the leading ethnic group in the country receives an amount of rainfall more than 2 Standard-Deviations above the average level it received over the period 1982-2001. **I(Rain$< \bar{r}_i$)** is an indicator variable that takes on value of 1 when the ethnicity receives less rainfall than its average over the study period.

Appendix D – Additional Robustness Checks

In this appendix we describe more in details the additional robustness checks that are mentioned at the end of Section 4.

Extended Period First, given that on rainfall and and ethnic conflicts (but *not* on the vegetation index) goes back to the 60s, we can assess the robustness of our result by extending the analysis also to previous decades. In doing so, we assume that the growing season over the period 1960-1981 was the same as the average growing season observed during the period 1982-2001. This is clearly a strong assumption. Moreover, as mentioned in the data section, it is only towards the end of the 70s that satellite images became available, and rainfall estimates for previous years should be considered much less reliable. Keeping these caveats in mind, Table D.1 replicates Table 2, extending the analysis to consider the 42 years from 1960 until 2001. Although the point estimate decreases, the coefficient remains large and significant.

Within-Group Inequality In order to further check that our results truly stem from inequality *between* ethnic groups living within the same country, we construct an alternative rainfall-based inequality variable that captures instead inequality *within* ethnic groups. To construct this *Within-Group Rainfall Inequality* (WGRI) measure we proceed in two steps.[1] First, we construct a group-specific measure of inequality by comparing rainfall across different areas within each ethnic group's homeland. The areas are defined by the 1.25 $\times$ 1.25 degree grid-cells in which rainfall data is provided by the ECMWF. The formula – similar to the one adopted for our BGRI – is

$$WGRI_i = \frac{1}{2r_i} \sum_{k=1}^{G_i} \sum_{l=1}^{G_i} \vartheta_k \vartheta_l \mid r_{i,k} - r_{i,l} \mid \tag{D.1}$$

where G_i is the number of rainfall grids that cover group i's homeland, $\vartheta_{i,l}$ indicates the relative size of grid-cell l^2, $r_{i,l}$ indicates the amount of rain that fell over that grid-cell, and r_i indicates the amount of rain that fell over the homeland of ethnic group i. To obtain the country-wide measure of within-group inequality, we then take the weighted sum of the group-specific inequality measures as

$$WGRI = \sum_{i=1}^{E} n_i \frac{r_i}{\sum_{j=1}^{E} r_j} WGRI_i \tag{D.2}$$

where the weights are given by the relative group size and relative group rainfall in the country.

We then run our standard regression, including both measures of inequality. For further check, we also include the *National Rainfall Inequality* (NRI) measure already de-

[1] This is adapted from the approach followed by Huber and Mayoral (2014).

[2] The weighting takes into account that some grid-cells are not fully included within a country, as country borders typically cut through some cells.

scribed in the main text.[3] Regressions 1 to 3 in Table D.2 show that the effect of a more unequal distribution of rain on ethnic conflict prevalence acts only through differences across ethnic lines. There is no evidence of any effect for WGRI and NRI, neither when they are considered alone, nor when they are jointly included in the same regression with BGRI.[4]

Additional Controls We next consider a set of additional determinants of conflicts that have been proposed in the literature (regression 4).[5] We start by considering GDP per capita, population size and years of peace, which have been defined by Hegre and Sambanis (2006) as the three core variables for cross-country civil conflict models.GDP per capita is meant to capture the economic conditions of the country and the opportunity cost of conflict (Fearon and Laitin, 2003; Collier and Hoeffler, 2004). Population size matters if one believes that there is a constant per capita propensity to participate in a conflict. Moreover, in order to enter the PRIO/Uppsala database an armed conflict needs to reach the threshold of 25 fatalities, which, *ceteris paribus*, is more likely to be reached when larger populations are involved. Finally, the number of years of peace captures the accumulation of peace-specific capital. In order to construct this last measure we start counting the years of peace since 1960 – i.e. the first year in which a civil conflict is recorded in Africa in the PRIO/Uppsala database – and we model the variable as a decay function of time at peace, following the approach used by Hegre and Sambanis (2006). We also include a control for openness to trade, as some scholars have suggested a link between trade and civil conflicts (Hegre et al., 2003; Elbadawi and Sambanis, 2002), and for gross aid inflows, as recent studies have found that aid can have perverse effects on civil conflicts prevalence (Nunn and Quian, 2014). Measures of democracy have also been often proposed as determinants of civil conflicts (Gurr, 2000; Hegre and Sambanis, 2006) and we therefore include an indicator variable for whether the country is under an autocratic regime, as indicated by a POLITY IV score below -5. We then also include a control for the (logarithm of) the total number of individuals affected by natural disasters in the country – as it might be correlated with both extreme climatic situations and the likelihood of conflicts – and for the two country-wide measures of yearly (log) rainfall and temperature. Finally, in a recent paper Morelli and Rohner (2015) show that ethnic wars (i.e. ethnic conflicts with more than 1000 fatalities) are more likely when oil and gas resources are unevenly distributed across ethnic groups within a country. We follow their approach and use the geo-referenced petroleum dataset provided by Lujala et al. (2007) to construct a Gini-based measure of resource inequality.[6] Although, allegedly some of these

[3]Just as a reminder, the approach followed in the construction of the NRI measure is similar to the one used in the first step for WGRI, with the difference that in this case we compare areas across the whole country, rather than focusing on specific ethnic groups' homelands. The formula is therefore given by $NRI = \frac{1}{2\bar{r}} \sum_{k=1}^{G} \sum_{l=1}^{G} \pi_k \pi_l \mid r_k - r_l \mid$, where G indicates the total number of rainfall grids covering the country, while π_k is the relative size of grid-cell k.

[4]Table C.3, in Appendix C, reports the correlation matrix for all the country-wide inequality variables used in the empirical analysis.

[5]We lose four observations due to incomplete data on trade openness.

[6]It should be noted that there are only 18 countries in our sample that host oil or gas fields (the variable takes always value zero for all other countries). Moreover, temporal variation is given by the discovery of

controls are likely to suffer from endogeneity, results in regression 4 show that our result is strongly confirmed.

Besides a country's own characteristics, the situation in neighboring countries may also play an important role. Here the literature is divided; while some studies find that civil conflicts tend to fuel violence in neighboring regions and countries (Sambanis, 2001; Harari and La Ferrara, 2014), others do not find any significant spill-over effects (Fearon and Laitin, 2003). To be cautious, we include two variables that are meant to capture the presence of *bad neighbors*: the share of neighboring countries with an ongoing ethnic conflict and the share of neighboring countries with an autocratic regime (again measured by a POLITY IV score below -5). Once again, the coefficient of interest remains virtually unaffected (regresson 5).

In regression 6 we include all the controls mentioned above in the same regression. Despite the risk of "bad controls" and the warning by Dell et al. (2014) against over-controlling in empirical models investigating the impact of climatic variables, the magnitude and significance of the coefficient of interest remains once again very stable.

In regression 7 we address the concern that the controls we considered might have a delayed effect on the incidence of conflicts, by also including a lag for each one of the variables just described (with the only exception of the variable capturing the number of years of peace). Although the point estimate of interest slightly decreases, it remains positive and statistically significant, once again confirming our results.

Conflict Onset Finally, part of the conflict literature focuses on conflict onset. While from a theoretical point of view a rise in rainfall-based inequality might both spur conflict initiation and fuel an ongoing conflict, in regression 8 we check whether the result holds when limiting the focus on conflict onsets. We construct the dependent variable following standard practice in the literature, coding consecutive years of conflict as missing, given that countries in conflict are not at risk of having a new onset (see for instance Collier and Hoeffler, 2004; Hegre et al., 2001; Sambanis, 2001; Buhaug and Rød, 2006). Although we lose almost 15% of the observations, the estimate shows that an increase in BGRI leads to a significantly higher risk of ethnic conflict onset (coefficient=0.523, p-value=0.072).

Overall, our results are confirmed across this additional set of robustness checks.

new fields, which only happens for 4 countries in our sample during the period under consideration.

Table D.1: Main effects at the country level, 1960-2001

Dependent Variable:	Ethnic Conflict					
	(1)	(2)	(3)	(4)	(5)	(6)
BGRI, growing season	0.324**	0.444**	0.344*			0.717**
	(0.160)	(0.225)	(0.189)			(0.342)
BGRI, growing season (t-1)			0.272			
			(0.172)			
BGRI, growing season (t-2)			0.207			
			(0.213)			
WGRI, growing season				0.096		0.388
				(0.134)		(0.336)
NRI, growing season					0.248	−0.362
					(0.153)	(0.363)
Country Effects	no	yes	yes	yes	yes	yes
Year Effects	no	yes	yes	yes	yes	yes
Country Time Trends	no	yes	yes	yes	yes	yes
R^2	0.05	0.51	0.51	0.50	0.51	0.51
N	1764	1764	1764	1764	1764	1764

Note: All inequality measures have been normalized by taking $(X - X_{min})/(X_{max} - X_{min})$. **Ethnic Conflict** is an indicator variable that takes on the value of 1 if a country experienced ethnic conflict in a given year. **BGRI** indicates Between-Group Rainfall Inequality. **WGRI** indicates Within-Groups Rainfall Inequality. **NRI** indicates National Rainfall Inequality. The sample includes 42 African countries and 42 years (1960-2001). Two-way clustered standard errors by year and country in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.2: Robustness checks II

Dependent Variable:	Ethnic Conflict							Onset
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BGRI, growing season	0.957*			0.697**	0.702**	0.708**	0.581**	0.523*
	(0.462)			(0.306)	(0.322)	(0.286)	(0.269)	(0.275)
WGRI, growing season	0.145	−0.103						
	(0.537)	(0.104)						
NRI, growing season	−0.327		0.290					
	(0.587)		(0.208)					
Ethnic Conflict (t-1)						0.369***	0.339**	
						(0.128)	(0.127)	
Additional Controls	no	no	no	yes	no	yes	yes	no
Neighbors Controls	no	no	no	no	yes	yes	yes	no
Lagged Controls	no	no	no	no	no	no	yes	no
Country Effects	yes	yes	yes	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes	yes	yes	yes
Country Time Trends	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.70	0.70	0.70	0.71	0.70	0.74	0.75	0.30
N	840	840	840	836	840	836	835	721

Note: All inequality measures have been normalized by taking $(X - X_{min})/(X_{max} - X_{min})$. **Ethnic Conflict** is an indicator variable that takes on the value of 1 if a country experienced ethnic conflict in a given year. **BGRI** indicates Between-Group Rainfall Inequality. *Additional Controls* refer to: (log) GDP per capita, (log) population, (log) individuals affected by natural disasters, (log) gross aid disbursements, openness to trade, autocracy indicator, years without conflicts, (log) rainfall, (log) temperature, Oil and Gas Gini. *Neighbor Controls* refers to the average prevalence of ethnic conflicts and the average autocracy indicator in neighboring countries. *Lagged Controls* refers to lags $t - 1$ for all control variables, with the only exception of the variable capturing the number of years without ethnic conflicts. We refer to the main text for a more detailed definition of the variables. The sample includes 42 African countries and 20 years (1982-2001). Two-way clustered standard errors by year and country in parentheses, adjusted for low number of clusters, using the number of years. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.