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

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Abstract

Does higher resource inequality between ethnic groups lead to higher ethnic civil conflict prevalence? In this paper, we empirically investigate this question by constructing a new measure of inequality, based on rainfall 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 ethnic civil conflict prevalence by 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 limited political power. By relying on an exogenous source of variation and a rich empirical specification, this paper establishes a causal link from inequality to conflict and presents novel evidence of the interaction between resource inequality and access to political power.

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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.[2] Economic inequality has been among the most debated dimensions in this literature. From a theoretical standpoint, inequality has been proposed as a driver of civil conflict at least since the time of Karl Marx, but it has proven very difficult to empirically demonstrate this relationship, mostly due to the lack of disaggregated income data.

In this paper, we construct a new measure of inequality based on rainfall data to investigate the relationship between inequality and conflict across Africa. The dataset covers 42 countries, over the time period 1982-2001 – i.e. the period for which all main data sources are available. Our strategy relies on rainfall directly affecting agricultural production, on which the livelihood of most people across the continent depended during the study period.

Given the high prevalence of ethnic conflicts across the continent, we focus on inequality along ethnic lines. The main hypothesis we test is whether an increase in inequality *between ethnic groups* leads to higher ethnic conflict prevalence. To this end, we combine high-frequency spatially disaggregated rainfall data with an historic map of ethnic group boundaries to calculate the yearly amount of rainfall for each ethnic group's homeland. There are 214 different ethnicities included in our sample. The key variable of interest is a country-wide Gini-type measure of *Between-Group Rainfall Inequality* (BGRI). We also use rainfall data to construct two alternative country-wide measures of inequality, namely *National Rainfall Inequality* (NRI) and *Within-Group Rainfall Inequality* (WGRI). The former does not take ethnic boundaries into account and is simply a measure of rainfall-based inequality across different geographic areas within a country, where the areas are defined

[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.

[2] Performing a sensitivity analysis of empirical results on civil conflict onset, Hegre and Sambanis (2006) identify 88 variables, grouped into 18 different "concept categories", that have been proposed in the empirical literature, mostly with conflicting results.

by the grids in which the rainfall data is provided. The latter is instead a measure of inequality within the same ethnic group.[3]

To substantiate our argument that rainfall-based inequality is related to economic inequality, we focus on rainfall during the plant-growing season, which is when rain matters the most for agricultural production and, hence, for income. Two tests support our approach. First, at the aggregated *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.[4]

Concerning the main empirical strategy, in the first part of the paper the unit of analysis is a country-year observation and the dataset allows controlling for year- and country-specific fixed effects, as well as country-specific time trends. To the best of our knowledge, this is one of the first studies on inequality and conflict to include such a rich set of fixed effects, dramatically reducing the risk of omitted variable bias.[5]

Results indicate a large and significant effect of BGRI on ethnic conflict prevalence. We find that a one standard-deviation increase in BGRI increases ethnic conflict prevalence by 0.43 standard-deviations. We find no effects for NRI or WGRI, indicating that ethnic conflicts are only affected by changes in the distribution of rainfall *between* different ethnic groups. Consistent with the proposed link with agricultural income, we the effect entirely stems from rainfall during the growing season. Reassuringly, the effect disappears when we consider non-ethnic conflicts.

This result passes a large set of robustness checks. First, we rule out that the BGRI measure simply captures ethnic polarization, or that the result is simply driven by inequality across administrative regions. Second, we address a number of potential threats to our identification strategy by including a battery of controls. Among these are rainfall along the main roads, malaria incidence, previous conflict history, and neighboring country characteristics. Importantly, across our sample, the BGRI measure is a much stronger

[3]As shown below, the country-wide measure of within-group inequality is obtained in two steps. First, a group-specific inequality measure is computed by comparing different geographic areas within the same ethnic homeland's boundaries. Second, the group-specific measures are aggregated at the country level through a weighted average.

[4]As satellite images on nightlight density are only available from 1992 onwards, our check covers the period 1992-2001.

[5]The only other work we are aware of, is a recent paper by Morelli and Rohner (2015), described in more details below.

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).

Overall, our results provide clear evidence that rainfall-based inequality is an important determinant of ethnic conflicts. Anecdotal evidence has however often named deeper tensions between ethnic groups – typically related to struggle over power – as the ultimate cause of conflicts, with temporary shocks and climatic factors mostly exacerbating these tensions (USAID, 2013). In the second part of the paper we therefore investigate whether and how the observed relationship between ethnic inequality and conflict depends on the way power is distributed across ethnic groups. We do so by relying on the Ethnic Power Relations (EPR) dataset, provided by Girardin et al. (2015). The dataset has smaller coverage than our main dataset (it only includes 37 of our 42 original countries) and a somewhat different definition of ethnic groups, but – among other things – it tracks the level of access to executive power for the groups over time. After replicating our previous results with the new dataset – which *per se*, constitutes an additional, powerful robustness check – we show that the results are driven by changes in the distribution of rainfall between the politically most powerful ethnic group and the other groups.

To better disentangle the mechanism behind these results, we complement the analysis at the country level with an analysis at the (country-)ethnicity level, relying on the information contained in the rich EPR dataset. Our results show that non-leading ethnic groups are more likely to be involved in an ethnic civil conflict whenever they receive *less* rain than the leading group. We do not find evidence for an increase in conflict prevalence when they receive *more* rain. 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.

Overall, the analysis at the ethnicity level confirms that rainfall-based inequality is a strong predictor of ethnic conflicts. It moreover shows that the link between inequality and conflict strongly depends on the specific power relations among the different ethnic groups. 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.

Limitations and Implications Our study has some limitations. Traditionally, economic inequality is considered something relatively persistent, as wealth typically changes only slowly over time. Our measures of inequality capture instead short-term changes in the distribution of (agricultural) resources, caused by exogenous year-on-year changes in the

distribution of rainfall. This should be kept in mind when interpreting our results, as it means that our inequality measures are ill-suited to test hypotheses related to persistent economic gaps within the society.[6] Moreover, in the absence of disaggregated income data, we are only able to look at the direct effect of rainfall distribution on conflict prevalence. We provide a number of checks that suggest that the exogenous variation we capture maps indeed into variation in income, but we cannot fully rule out that the link between rainfall inequality and conflicts also involves 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. Climate change has indeed been shown to be associated, among other things, with higher short-term weather variability and more extreme weather conditions (Semenov and Barrow, 1997; IPCC, 2014). These are likely to lead to larger variations in the distribution of rainfall across different areas, thus potentially increasing the risk of ethnic conflicts. While further analysis is needed to identify the most appropriate response, our study indirectly suggests that interventions that make the agricultural system less dependent on climatic conditions (e.g. through extended irrigation systems), as well as national policies providing compensation for groups negatively affected by relatively worse weather, might help reducing the risk of ethnic civil conflicts. Finally, our analysis suggests that political representation can play a key role in settling ethnic tensions, as we find that groups that have access to some political power are significantly less likely to engage in armed conflict as a response to an increase in resource inequality that penalizes them.

Contributions to the Literature Our work combines three different strands in the conflict literature: the literature on economic inequality, on climate, and on ethnic politics – providing a contribution to each one of them.

First of all, our paper speaks to the long-standing literature on the relationship between inequality and armed conflicts.[7] 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 either unlikely to provide exogenous variation, or available just for a few

[6] Esteban and Ray (2008), for instance, propose that (persistent) economic gaps within groups can lead to higher risk of intra-group conflicts due to the creation of a rich elite, that can finance the conflict against another group, and a poor mass, that can fight it. The fact that we only capture short-term changes in the distribution of resources might partly explain why we find instead no effect of an increase in within-group inequality on ethnic conflict prevalence.

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

years.[8] In this paper we tackle the endogeneity issue and circumvent the lack of disaggregated income data, by constructing new inequality measures based on high-frequency rainfall data.[9]

In doing so, we borrow insights from the literature on climate and conflict, which has grown fast in recent years, following the seminal paper by Miguel et al. (2004). Across a large number of settings, this literature has found that areas that experience worse climatic conditions than usual are also likely to experience higher risk of conflict (for a review, see Burke et al. (2015)).[10] 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 across different areas of a country, thereby introducing a new and so far neglected dimension in the analysis. 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).[11]

Finally, a growing body of studies has investigated the role of power relationships across ethnic groups, finding that grievances in groups that are excluded from power are

[8]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). Secondly, 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, therefore, are likely to be under-represented in the data, further biasing the analysis. Concerning nightlight density and economic activity data (i.e. the G-Econ dataset developed by Nordhaus (2001)), on top of potential endogeneity issues, the datasets are only available for a limited number of years. Kuhn and Weidmann (2013), for instance, only rely on 1992 nightlight density data for their study, while Cederman et al. (2011) only rely on 1990 information on economic activity.

[9]The work that is the closest to our approach is a recent paper by Morelli and Rohner (2015), in which the authors consider a time-varying ethnic inequality measure based on the location of oil and gas fields within a country, finding that higher inequality is associated with higher risk of conflict. To the best of our knowledge, this is the only other paper on inequality and conflicts to employ a rich empirical specification with year and country fixed effects. There are however significant differences compared to our work. First of all, while Morelli and Rohner rely on a larger sample of 157 countries over the period 1960-2008, their measure of inequality only takes positive values for countries that have access to oil and gas. Second, variation in their inequality measure stems from the discovery of new fields. Although the authors discuss why this should not pose a major threat to the analysis, we believe that using rainfall data addresses more convincingly any endogeneity concern.

[10]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 and for references to the lively academic debate provoked by an empirical paper by Burke et al. (2009) on the relationship between temperature and civil wars in Africa.

[11]Along the same lines, in a recent paper, Ralston (2015) uses micro level data to show 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.

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 defines the measures of rainfall-based inequality. Section 5 illustrates the empirical framework. Section 6 presents and discusses the results concerning the impact of rainfall inequality on ethnic conflicts. Section 7 looks at the role of power relations among ethnic groups, introducing new inequality measures and presenting the related results. Finally, Section 8 concludes.

2 Conceptual framework

The link between economic inequality and armed conflicts has its foundation in 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 in society. 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 fundamental factors such as language, race, or religion (Horowitz, 1985; Østby, 2008; Esteban and Ray, 2008).[12] From a theoretical point of view, both higher inequality *between* and *within* ethnic groups might lead to higher risk of ethnic conflicts. Inequality between groups might facilitate mobilization for conflict by enhancing grievances between the

[12]In Africa in particular, the identification with ethnicities often trumps national identity due to the relatively short national histories and to the often arbitrary national boundaries of many African countries (Michalopoulos and Papaioannou, 2014; Francois et al., 2015).

different groups and increasing cohesion within the same group (Østby, 2008). Inequality within groups might instead facilitate mobilization for conflict by leading to the creation of a rich elite that can finance the conflict and a poor mass, with low opportunity cost, that can fight it (Esteban and Ray, 2008). As mentioned in the introduction, the main challenge for empirically testing these links is the lack of disaggregated income data at the group level .

This is where the link between climate and income comes in. In most developing countries the majority of individuals directly depend on agriculture for their livelihoods, and agricultural output is highly dependent on climatic conditions.[13] As a consequence, within developing settings, changes in the pattern of climatic variables are strong predictors of changes in income, and have been extensively used as such in the empirical literature (e.g. Miguel et al., 2004; Miguel, 2005; Jia, 2014).[14] Given that climatic variables are available with high frequency and in a disaggregated form, we rely on them to construct our inequality measures. These measures – to be formally presented in section 4 – are meant to capture year-on-year variations in the distribution of rainfall between ethnic groups (*Between-Group Rainfall Inequality*), within ethnic groups (*Within-Group Rainfall Inequality*), and across the country (*National Rainfall Inequality*). The main hypothesis is that an increase in resource inequality between ethnic groups leads to higher conflict prevalence. We do not expect any effect for within-group inequality – as the mechanism proposed by Esteban and Ray (2008) rests on permanent differences in income that are not captured by our measure – nor for national inequality, which is the measure most closely related to the standard individual Gini measure that does not take groups into account. As we focus on inequality demarcated along ethnic lines, we expect to find an impact specifically on ethnic conflicts.[15]

Ethnic conflicts are however often described as the violent manifestation of long-

[13]This is particularly true for Africa. In 2004, some 55% of the people in the continent were employed in agriculture and many more indirectly depended on it, while only 6.4% of cultivated land in Sub-Saharan Africa was irrigated (Frenken, 2005)

[14]For completeness, it should be mentioned that recent economic literature has shown climate to affect a number of socio-economic outcomes other than income (for a comprehensive review see Dell et al., 2014). This has brought into question the appropriateness of empirical studies that use climatic variables as an instrument for income, as the exclusion restriction might not be satisfied (Sarsons, 2015). The reduced-form results that we will discuss in the following chapters should therefore be interpreted as the gross effect of changes in the distribution of rainfall on ethnic conflict, potentially operating through multiple channels. We will in any case do our best to refine the definition of the rainfall variable to only capture that amount of rain that matters for income-generating activities, and we will present some tests providing suggestive evidence that this is indeed the case.

[15]This represents a further improvement compared to most previous studies, which considered civil conflicts as an aggregate category, despite theoretical and empirical works showing fundamental differences in the origins of ethnic and non-ethnic conflicts (Sambanis, 2001; Sambanis and Shayo, 2013).

standing tensions between ethnic groups, typically founded on competition over access to state power in countries with weak political institutions.[16] Control over state power has indeed 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 the 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 grievances, leading to a further increase in the risk of armed violence.[17] In the second part of the paper we therefore consider the interplay between rainfall-based inequality and the specific power relationships among the different ethnic groups. The hypothesis we test is whether ethnic groups excluded from power are more likely to engage in ethnic conflict whenever a change in resource distribution penalizes them with respect to the leading group.

3 Data

We combine information from several different sources to construct the dataset, which comprises 42 African countries.[18] Based on data availability (see below), our analysis covers 20 years, from 1982 to 2001. Table 1 reports the list of countries included in the study. Summary statistics for the variables used in the first part of the analysis are reported in Table 2, while statistics related to the variables used in the second part will be reported in Table 9. 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.

[16] For instance, Horowitz (1985) writes that "*The permeative character of ethnic affiliations, by infusing so many sectors of social life, imparts a pervasive quality to ethnic conflict and raises sharply the stakes of ethnic politics. [...] In divided societies, ethnic conflict is at the center of politics.[...] Ethnic conflict strains the bonds that sustain civility and is often at the root of violence that results in looting, death, homelessness, and the flight of large number of people. In divided societies, ethnic affiliations are powerful, permeative, passionate, and pervasive.*"(pp. 7, 12).

[17] One possibly complementary interpretation, consistent with a less favorable distribution of resources for the excluded groups leading to higher risk of 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.

[18] We exclude from the analysis 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 (results available on request)

3.1 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 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 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.[19] Table 1 details for each country the number of years of ethnic and non-ethnic conflicts over the period under consideration, while Figure 1 visually illustrates of their distribution across the continent.

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 ethnic groups around the world as of the early 1960s. The GREG map has already been extensively used in the economic literature (Easterly and Levine, 1997; Esteban et al., 2014; Alesina et al., 2014). Our dataset includes 214 different ethnicities, with an average of 11 (median is 10) different ethnicities per country (see Table 1).

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 reflects 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, replicating our main result with an alternative *dynamic* set of digitalized maps, provided by Wucherpfennig et al. (2011). The Geo-referencing Ethnic Power Relations (GeoEPR) maps trace the location of the ethnic groups included in the EPR dataset (described below) over time. Differently from the GREG map, the Geocoded EPR map does not portray ethnic *homeland*, but rather

[19] This is the same criterion used by the Wimmer et al. to define ethnic conflicts. 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).

the actual occurrence of ethnic group members in a specific region. The classification and localization of ethnic groups is based on expert panels and is somewhat different from those adopted in the GREG map. Moreover, the GeoEPR map has smaller coverage than the GREG map.[20] We therefore conduct the main analysis with the full sample provided by the GREG dataset and rely on the GeoEPR map to test the robustness of our results in the second part of the paper, keeping in mind the caveat concerning endogenous movements of ethnic groups.

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.[21] As mentioned above, the classification of ethnic groups is somewhat different from the one adopted in the *Soviet Atlas*. Whenever using the EPR dataset we therefore rely on the GeoEPR map provided by Wucherpfennig et al. (2011).

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 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.

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. 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, as they can never fight the central state, which is under their sole control.

[20] The following countries are missing from the Georeferenced EPR dataset: Burkina Faso, Somalia, Swaziland, and Tunisia. Moreover, Uganda has no ethnic group mapped until 1985, while Zimbabwe has no groups mapped until 1991.

[21] 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).

Rainfall A wide range of rainfall data sources are available to researchers, each with its advantages and disadvantages.[22] 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). The dataset provides re-analysis 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.[23] 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 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). 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 developed by Jönsson and Eklundh (2004) – two Swedish ecologists – 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 season within each rainfall grid-cell. The average rainfall during the growing season for each ethnic group and country is then obtained by overlaying the grids with the spatial ethnicity and administrative maps. Figure 2 and 3 visually illustrate the way the different data sources are combined when considering the GREG and the GeoEPR maps, respectively.

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 also provide a validation check, showing that at the country level

[22] See Dell et al. (2014) for a discussion on this matter and for a list of the main sources used by economists.
[23] See Kudamatsu et al. (2014) for a discussion of the advantages of this source over alternatives.

our measure of 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.[24]

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 used as such in the recent economic literature, mostly due to the lack of better alternatives.[25] 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 kilometres at the equator. We first compute average nightlight density for each of our 1.25 $\times$ 1.25 degree cells (defined by the rainfall grid) and then compute nightlight density inequality measures in the same way as we compute the rainfall inequality measures.[26]

In one of our robustness checks we also include a measure of *temperature-based inequality* during the growing season. This is meant to limit the risk of omitted variable bias, in light of the typically high correlation across climatic variables (Burke et al., 2015). To build this variable we rely on the temperature data that is made available by the ECMWF with the same frequency (six hours) and resolution (1.25 $\times$ 1.25 degrees) as the rainfall data. The variable is constructed in a similar way as the rainfall-based inequality measure.

Especially in Sub-Saharan Africa, rainfall is expected to directly affect *malaria preva-*

[24]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).

[25]Henderson, et al. (2012), Chen and Nordhaus (2011), Pinkovskiy (2013), Pinkovskiy and Sala-i-Martín (2014), Hodler and Raschky (2014), Michalopoulos and Papaioannou (2013, 2014), Kuhn and Weidman (2013), Alesina et al. (2014).

[26]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.

lence, 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 1.25×1.25 degree grid-cell we 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.

We also construct a measure of *rainfall-induced transport 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 digitalized 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 then compute the yearly amount of rainfall over each buffer.[27] Finally, we weight the road-specific rainfall measure by each road's relative length to obtain the country-wide average.

In our 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 widely used Polity IV database (see for instance Fearon and Laitin, 2003, and Hegre and Sambanis, 2006), provided by the Center for Systemic Peace (Marshall et al., 2013). Figures on *aid inflows*, recorded as gross disbursement in constant USD dollars, is taken from the Creditor Reporting System database kept by the OECD. 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). 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).

[27] 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.

4 Rainfall-Based Inequality Measures

By combining the main datasets described above, we generate three rainfall-based inequality measures.

The first measure is *Between-Group Rainfall Inequality* (BGRI). BGRI is inspired by the standard Gini coefficient, and is computed, for each year, as the weighted average of the differences in rainfall among ethnic groups within a country, where the weights are given by the relative size of each ethnic group.[28] The measure is normalized by the average amount of rainfall in the country, to allow for comparisons across countries. More formally, the index is constructed for each country and year as (omitting time and country indicators):

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

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, r_i is the amount of rain that fell over ethnic group i's homeland, and $\bar{r}$ is the average amount of rainfall that fell over the whole country in that year.[29] In order to account for group-specific variations in climatic conditions, in a robustness check we replace the level of rainfall r_i with the deviation from the group-specific average rainfall over the period 1982-2001, expressed in standard-deviations, i.e. $(r_i - \tilde{r}_i)/SD_{r_i}$.[30]

The second measure is *Within-Group Rainfall Inequality* (WGRI). In this case we proceed in two steps.[31] 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 1.25×1.25 degree grid-cells in which rainfall data is provided by the ECMWF. The formula – similar to the previous one – is

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

where G_i is the number of rainfall grids that cover group i's homeland, $\vartheta_{i,l}$ indicates the

[28] 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.

[29] Figure B.1 in Appendix B illustrate for each country the average and standard-deviation for the BGRI measure, based on rainfall during the growing season, over the period 1982-2001.

[30] As measures are expressed in terms of standard-deviations, in this case we do *not* divide the weighted sum by the average rainfall in the country $\bar{r}$.

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

relative size of grid-cell l[32],$r_{i,l}$ indicates the amount of rain falling on that grid-cell, and r_i indicates, as before, 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

$$WGRI = \sum_{i=1}^{E} n_i \frac{r_i}{\sum_{j=1}^{E} r_j} WGRI_i, \tag{3}$$

where the weights are given by the relative group size and relative group rainfall in the country.[33]

Finally, we also compute a measure of *National Rainfall Inequality* (NRI). The approach 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

$$NRI = \frac{1}{2\bar{r}} \sum_{k=1}^{G} \sum_{l=1}^{G} \pi_k \pi_l \mid r_k - r_l \mid, \tag{4}$$

where G indicates the total number of rainfall grids covering the country, while π_k is the relative size of grid-cell k.[34]

5 Empirical Framework

We start our analysis by investigating the impact of resource inequality on the incidence of ethnic conflicts across 42 African countries over the period 1982-2001. The use of rainfall-based measures addresses the problem of reverse causality in our empirical analysis, but generates the concern that, apart from affecting (agricultural) resources and income, rainfall might have other direct consequences on ethnic conflict prevalence. We try to ease this concern in different ways. First, as already mentioned above, in constructing our inequality measures we exploit the fact that rain is most "productive" when it falls during the growing seasons (and we will provide suggestive evidence that this indeed the case). Second, thanks to the yearly frequency of our data, in our empirical specification we con-

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

[33]Figure B.2 in Appendix B illustrate for each country the average and standard-deviation for the WGRI measure, based on rainfall during the growing season, over the period 1982-2001.

[34]Figure B.3 in Appendix B illustrate for each country the average and standard-deviation for the NRI measure, based on rainfall during the growing season, over the period 1982-2001.

trol for a large set of fixed effects, significantly decreasing the risk of omitted variable bias. Finally, to cut off additional potential confounding effects, in our robustness checks we explicitly control for a rich set of variables.

Validation Checks We start by checking whether our measure of rainfall during the growing season is indeed associated with agricultural production and wealth. Unfortunately, the lack of systematic disaggregated data forces us to rely on two indirect tests. First, we check whether yearly rainfall during the growing season predicts agricultural output at the *country* level, by running the following regression:

$$(5) \qquad AgricOutput_{c,t} = \alpha_1 log(rain_{gr})_{c,t} + \alpha_2 log(rain_{nongr})_{c,t} + \varphi_c + \pi_t + \vartheta_c t + \varepsilon_{c,t},$$

where the dependent variable is a measure of agricultural output (cereals, crops, agriculture, or food), recorded by FAO on a yearly basis (t) for each country (c). $Rain_{gr}$ is our variable of interest and indicates the amount of rain that fell during the growing season, for each country and year, while $rain_{nongr}$ captures rainfall outside the growing season. Our approach suggests that we should expect $\alpha_1 > 0$ and $\alpha_2 \sim 0$. φ_c and π_t indicate country- and year- fixed effects, respectively, and $\vartheta_c t$ indicates country-specific linear time trends.

While this first check helps us to validate our measures of rainfall and growing season at the country level, it does not say much about the link between rainfall and wealth at a more disaggregated level. We therefore perform a second test, exploiting data on nightlight density, which represents the only alternative proxy for economic activity that is available in a disaggregated form and on a yearly basis (since 1992). In this case we proceed in two steps. First, we test whether at the *ethnic group* level (log) rainfall during the growing season is positively associated with (log) nightlight density per capita, by running the following regression:

$$(6) \quad log(nightlight)_{e,c,t} = \delta_1 log(rain_{gr})_{e,c,t} + \delta_2 log(rain_{nongr})_{e,c,t} + \gamma_e + \rho_c + \mu_t + \theta_c t + \epsilon_{e,c,t},$$

where we also include ethnicity fixed effects γ_e. Our hypothesis, once again is that $\delta_1 > 0$ and $\delta_2 \sim 0$. Second, we test whether at the *country* level between-group rainfall inequality during the growing season (BGRI) maps into between-group nightlight inequality

(BGNI)[35], by running the following regression:

$$BGNI_{c,t} = \beta_1 BGRI_{c,t} + \psi_c + \varsigma_t + \omega_c t + v_{c,t}. \tag{7}$$

In this case the coefficient of interest is β_1 and we expect it to be positive.

Main Specification Our main specification captures the reduced-form relationship between rainfall-based inequality and the prevalence of ethnic conflict. The corresponding empirical model is:

$$EthnicConflict_{c,t} = \lambda_1 Inequality_{c,t} + \Psi \mathbf{X}_{c,t} + \tau_c + \phi_t + \kappa_c t + \eta_{c,t}, \tag{8}$$

where the dependent variable is an indicator taking on the value of 1 if country c experienced ethnic conflict in year t, $Inequality$ indicates one of our three measures of rainfall inequality and $\mathbf{X}$ is a vector of controls that will be detailed below. The 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 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 international 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. The coefficient of interest is λ_1 and a positive coefficient indicates that higher levels of inequality lead to higher ethnic conflict prevalence. In our analysis we always report standard errors clustered by country and year, to account for the possibility that observations are correlated over time for the same country and across countries for the same year.[36]

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, for two reasons. First and most impor-

[35] As mentioned above, BGNI is calculated in the same way as BGRI, using nightlight density per capita instead of rainfall.

[36] 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).

tantly, a logit model would force us to exclude countries that never experienced any ethnic conflict, thus potentially leading to selection bias. Second, OLS estimates are easier to interpret, and – since they typically give similar results as logit ones – are often preferred in the literature (Beck, 2015).

6 Results

6.1 Validation checks

We start our analysis by running model (5), to check whether rainfall during the growing season is indeed associated with agricultural production. We consider all the four key 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, and no matter whether rainfall outside the growing season is included in the model or not (regressions 1 to 8). Furthermore, and again consistent with our conjecture, results show that rainfall outside the growing season bears no link with agricultural output (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 0.54 standard-deviation increase in the production index.

As a second step, we investigate whether our rainfall measure is associated with economic activity at the sub-national level. 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, and it is moreover only available since 1992. With these caveats in mind, Table 4 shows the results. We start by running model (6). 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 estimate is less precisely estimated and falls just above the threshold for being significant at 10% level (p-value 0.103). Regressions 3 to 5 report the results for different specifications of model (7). Regression 3 shows a positive and significant relationship between BGRI and BGNI at the country level. Consistent with our

previous findings, the relationship is entirely driven by rainfall during the growing season (regression 4), while the coefficient on BGRI outside of the growing season is small (0.016) and not statistically significant (p-value 0.474). Finally, 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 is not statistically significant (regression 5).

6.2 Main Results

We now test whether BGRI has an effect on ethnic conflict prevalence, by running model (8). Table 5 reports our main results. Regression 1, without any controls, shows a significant 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 is 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 0.43 standard-deviation increase in ethnic conflict prevalence.

The effect 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).[37] Regressions 4 to 6 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.[38] Overall, these results provide support for the hypothesis that between-group inequality has a significant impact on the prevalence of ethnic civil conflicts.

Falsification Tests We next perform a number of falsification tests, reported in Table 6. To make comparison easier, regression 1 repeats the main result from Table 5.

We start by testing our strategy using rainfall outside the growing season, that is, when rainfall is less relevant for agricultural production and, hence, for income. Reassuringly, regressions 2 and 3 show that inequality based on rainfall outside the growing season has

[37] 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.3, Appendix C).

[38] Table C.2, in Appendix C, reports the correlation matrix for all the country-wide inequality variables used in the empirical analysis.

no effect on ethnic conflict prevalence, neither when it is considered alone (regression 2), nor when it is included in the same regression as our BGRI measure during the growing season (regression 3).

An additional concern is that our ethnic homeland data might simply be picking up administrative unit boundaries – potentially affecting the interpretation of our analysis. To ease this concern we re-compute our BGRI measure using the 1990 level 1 administrative borders provided by GAUL.[39] The new measure does not have any significant effect on ethnic conflict (regression 4). Furthermore, a horse-race with our original ethnicity-based measure is clearly lost (regression 5).

Finally, since our measure focuses on ethnic inequality, it should not be able to predict non-ethnic conflict. In line with this conjecture, regression 6 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.

Robustness checks We then run a set of robustness checks. Results are reported in Table 7. Again, regression 1 shows the main result from Table 5 to make comparison easier.

We start by considering an alternative definition of our BGRI measure in regression 2. Instead of using differences in rainfall levels across ethnic groups, we explicitly account for the local climatic conditions of each group and look at differences in deviations from each ethnic group average rainfall level, measured over the period 1982-2001. Although somewhat smaller, the estimated coefficient on the new variable remains positive and highly significant.

One might also be worried that our BGRI measure simply picks up ethnic polarization rather than rainfall inequality.[40] To test for this, we compute a measure of ethnic polarization, based on Montalvo and Reynal-Querol (2005).[41] We interact this country-specific

[39]Level 1 administrative units represent the largest sub-national administrative division, typically corresponding to regions or districts. The GAUL database only starts in 1990 and we therefore consider that year, which falls in the middle of our study period, for our analysis. It is worth noting that administrative boundaries are typically redefined over time, and their definition is likely to be partly endogenous to conflicts.

[40]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) is therefore going to matter for our measure. Although this does not represent a threat per se, because our identification stems from variation in the inequality measure over time within the same country, one might still be worried that our results are driven by settings where distribution is more polarized, as this would matter for the interpretation of our results.

[41]The index is constructed as $Polarization_c = 4\sum_{i=1}^{E} n_{i,c}^2(1 - n_{i,c})$ where $n_{i,c}$ is the relative size of ethnicity i in country c and E 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

polarization index with our NRI measure to test whether a more unequal distribution of rainfall across a country (captured by NRI) matters more in highly polarized settings. Our estimates suggest that polarization is not driving our results: the interaction term is not statistically significant and, if anything, negative, while the effect of BGRI remains large and significant (regression 3).

Next, we show that our results are also robust to excluding main urban areas (regression 4[42]), restricting the sample to Sub-Saharan Africa (regression 5), and restricting the sample to the 17 countries for which there is variation in the dependent variable (regressions 6). 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 our sample, our coefficient of interest remains stable, ranging from 0.488 to 0.818 (see Figure B.4, in Appendix B).

Finally, a large part of the conflict literature focuses on conflict onset, rather than on the presence of an active conflict. 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 7 we check whether our main result also holds when we 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 some observations (and power), BGRI is still positively and significantly associated with ethnic conflict onset.

In the second part of our robustness checks we enrich our empirical specification with a number of variables that have been proposed in the literature as drivers of civil conflicts. Results are reported in Table 8.

First of all, conflicts tend to be persistent over time. Many empirical studies thus control for a lagged conflict variable. Regression 1 shows that the lagged ethnic conflict variable is indeed a powerful predictor for current ethnic conflict, but the coefficient on the BGI measure is virtually unaffected.[43]

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.4, 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, the BGRI coefficient remains always positive, large, and significant across all regressions, while the interaction term is never significant.

[42]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.

[43]The inclusion of the lagged dependent variable in a fixed effects model risks generating the so called Nickell bias (Nickell, 1981). We therefore also re-estimated the regression using GMM estimators, instru-

In their comprehensive review of empirical studies on climate and conflicts, Burke et al. (2015) point out that temperature and rainfall are often correlated and recommend including both of them in the regressions to avoid omitted variables bias. In regression 2 we therefore include the 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 empirical studies also suggest that rainfall might reduce chances that troops face each other in combat due to more difficult transportation conditions and thus might have direct effects on conflict other than through income (Rogall, 2015). Moreover, 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 3 shows that our results are robust to including the measure of yearly rainfall along the main roads of the 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) use current and lagged country-wide measures of rainfall growth to instrument for economic 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.[44]

We next consider a number of additional potential determinants of conflicts that have been proposed in the literature (regression 5).[45] We start by considering GDP per capita, population size and years of peace, which have been defined by Hegre and Sambanis

menting the first lag of the dependent variable with the second lag. The estimate of the coefficient of interest remains virtually unchanged (see regression 3 in Table C.3, in Appendix C).

[44]Similarly to what we did in Table 5 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 and 5 in Table C.3, 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.3, in Appendix C).

[45]We lose four observations due to missing information for some variables.

(2006) as the three core variables for cross-country civil conflict models.[46] 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 was under an autocratic regime in a given year, 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. with more than 1000 fatalities) are more likely when oil and gas resources are unevenly distributed across ethnic groups within a country. We therefore 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.[47] Although, allegedly some of these controls are likely to suffer from endogeneity, results in regression 5 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 appears divided; while some studies find that civil conflicts tend to spill over into 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 controls, capturing the share of neighboring countries with an ongoing ethnic conflict and with an autocratic regime (again measured by a POLITY IV score below -5), which are supposed to proxy for *bad neighbors*. Once again, our coefficient of interest remains virtually unaffected.

In regression 6 we include all the controls mentioned above in the same regression,

[46] 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).

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

despite the risk of "bad controls" mentioned above and despite the warning by Dell et al. (2014) against over-controlling in empirical models investigating the impact of climatic variables. Our results show that the magnitude of the coefficient of interest remains once again very stable.

Finally, 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 highly statistically significant, once again confirming our results.

7 The Role of Ethnic Power Relationships

The results obtained so far show that temporary exogenous changes in the distribution of resources across ethnic groups significantly affects the risk of ethnic violence. Anecdotal evidence has however often identified deeper existing tensions between ethnic groups – typically related to struggle over power – as the ultimate cause of conflicts, with temporary shocks and climatic factors mostly exacerbating these tensions (USAID, 2013). In this section we therefore investigate whether and how the observed relationship between inequality and ethnic conflict depends on the specific way in which political power is distributed across the ethnic groups.

For this analysis, we rely on the information contained in the Ethnic Power Relations (EPR) dataset (Girardin et al. 2015) and in the associated GeoEPR set of digital maps (Wucherpfennig et al., 2011). As mentioned in the data section, among other things, the EPR dataset tracks the evolution of access to executive power for the different ethnic groups.[48] Based on this dataset – which covers 37 countries and 172 ethnicities – we construct a new country-level measure of inequality (detailed below) that captures yearly differences in the level of rainfall between the ethnic group with the most political power (i.e. the *leading* group) and the other groups. The analysis at country level, however, does not allow disentangling individual groups' behavior. Even when taking ethnic power relations into account, a rise in inequality can indeed lead to higher conflicts prevalence for different reasons. It might for instance be the case that a group that is excluded from (or has only limited access to) power displays a higher propensity to engage in conflict against the central state whenever it is relatively *better* off, as the increased wealth and

[48]The focus on executive power is justified by the fact that executive branch is where power is typically held and where decisions are taken, and this appears especially true across African countries (Barkan, 2008; Rainer and Trebbi, 2011). Moreover, legislative bodies are sometimes suppressed – for instance under military rules – making it harder to track their evolution over time.

resources might increase its chances of winning the conflict. But it might also be the case that the group displays a higher propensity to engage in conflict whenever it is relatively *worse* off, as it then experiences stronger grievances and/or has relatively less to lose from the conflict. As a last step, we therefore move to consider the (country-)ethnicity level, exploiting the information on the link between ethnic groups and rebel actors that is included in the EPR database.

7.1 Power-Adjusted Rainfall Inequality Measures

To take ethnic power relations into account we modify the original BGRI measure. Rather than comparing rainfall between every ethnic group within a country, we now compare rainfall between the leading ethnic group and the other groups. We 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.[49] We then define inequality for each country and year as

$$BGRI^{power} = \frac{1}{2\bar{r}} \sum_{i=1}^{E_{nonlead}} n^{LEAD} n_i^{NONLEAD} \mid r^{LEAD} - r_i^{NONLEAD} \mid, \tag{9}$$

where $E_{nonlead}$ indicates the number of non-leading groups in the country, and n and r indicate, as before, the relative size of the group and the amount of rainfall that fell during the growing season within the boundaries of the ethnic group, respectively. We also consider an alternative measure of $BGRI^{size}$, which defines the leading ethnic group on the basis of its population size, as recorded directly in the EPR dataset.

When we move to the analysis at the (country-)ethnicity level we build a group-specific measure of $RainfallInequality$ (RI) with respect to the leading ethnic group in the country, which we model on the basis of the country-level measure described above and defined as (omitting, as always, time and country indicators)

$$RI_i^{power} = \frac{1}{2\bar{r}} \mid r^{LEAD} - r_i \mid, \tag{10}$$

where, as always, 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

[49] 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.

the boundaries of the leading ethnic group living in the country. As before, the index is normalized using the average level of rainfall within the country.

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:

$$RI_i^{power-} = \begin{cases} \frac{1}{2\bar{r}}(r^{LEAD} - r_i) & \text{if } r^{LEAD} > r_i \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

$$RI_i^{power+} = \begin{cases} \frac{1}{2\bar{r}}(r_i - r^{LEAD}) & \text{if } r^{LEAD} < r_i \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

7.2 Results

Country-Level Analysis Table 9 reports the summary statistics for all the variables used in this second part of the analysis, based on the EPR dataset, which covers 37 countries and 172 ethnicities.[50] Given the differences between the EPR and the GREG datasets, we start by re-running our baseline specification to test whether the previous results are confirmed with the new dataset. Results are reported in Table 10.

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, and very close in magnitude to what we obtained with the GREG dataset (0.662 and p-value 0.073). 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. Regression 3 shows that the new BGRI measure based on equation (9) has a large and significant effect on ethnic conflict prevalence (1.074, p-value 0.01). A horse-race between this new measure and the original BGRI strikingly shows that inequality with respect to the leading group is what really 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).[51] Finally, in regression 4 we test the new between-group inequality measure, based on political power relations, against an alter-

[50] For more details on the specific countries, see Table C.1, in Appendix C.

[51] The correlation between the standard BGRI measure and the power-based measure is 0.7 (see Table C.2, in Appendix C).

native measure, in which the most powerful group is defined on the basis of population size – an alternative measure of the group's pure strength. The estimates clearly confirm that it is access to power that matters.

Ethnicity-Level Analysis In order to shed some light on the mechanisms, we move to perform the analysis at the (country-)ethnicity level. 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.[52] Results are reported in Table 11. All regressions also include a full set of ethnicity fixed effects, to take into account any time-invariant ethnic-specific characteristics.

The estimate in regression 1 mirrors the result observed at the country-level, confirming 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 – constructed as per equation (10) – leads to a significant 0.15 standard-deviation increase in the likelihood that the group engages in ethnic civil conflict.

While the inequality measures considered so far equally weighted positive and negative changes with respect to the main group's rainfall level, we now split the measure in the two variables described by equations (11) and (12). The estimate in regression 2 shows that an ethnic group is more likely to fight against the leading group when it receives relatively *less* rain. 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).[53]

Regression 5 shows that our result is robust to including a number of additional controls: whether the group has lost power in the previous year, whether the group is currently fully excluded from power (i.e. is neither a *Senior Partner* nor a *Junior Partner*), and the number of conflicts the group has been previously involved in (since its record in the EPR dataset). In line with previous findings in the literature (Cederman et al., 2010), all these variables significantly increase the chances that a group engages in ethnic conflict. We also include a variable capturing ethnic-specific variations in rainfall with respect to its average over the study period, expressed in standard-deviation units. While the coeffi-

[52] 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 ethnic group always take value 0.

[53] 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).

cient on this variable is negative, it is far from reaching statistical significance.[54] To further assess the robustness of our finding, we also repeated 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 quite stable, ranging from 0.052 to 0.113 (Figure B.5 in Appendix B).

So far, our sample also included ethnic groups classified as *Senior Partner* or *Junior Partner*, which therefore still detain some access to executive power. Recent evidence from the African continent has shown that political representation has often been used as an instrument to manage ethnic relations (Francois et al., 2015). We therefore check whether political representation helps containing the risk of conflict in the face of a rise in resource inequality. Results reported in Table 11 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).

Overall, these results indicate that groups with no access to power are more likely to engage in civil conflicts when they receive less rainfall than the leading ethnic group. This is consistent with the relative drop in resources both exacerbating grievances and making the conflict relatively more convenient for the excluded group. Unfortunately, the information at our disposal does not allow us to clearly pin down the exact mechanism and it seems likely that both grievances and opportunity-cost considerations reinforce each other. We attempt in any case to shed some more light on this point through an indirect check, by considering groups that recently lost political power. Grievances are likely to be particularly high in those settings and, if an exogenous rise in inequality further exacerbates them, we should expect a particularly pronounced effect in those situations. 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 in the EPR dataset.[55] The interaction coefficient is positive and highly significant. Per se, this result is also still consistent with a

[54] 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.5, in Appendix C).

[55] From the most to the least powerful group, the scale goes: *Monopolist*, *Dominant*, *Senior Partner*, *Junior Partner*, *Powerless*, *Discriminated*. Table C.5, 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 a simple 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).

pure opportunity-cost story, as the recently downgraded ethnic group might find it easier to mobilize group members for the conflict 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 it also receives less rain than usual. Indeed, while for the *relative deprivation* theory (Gurr, 1970) 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 consideration should improve – all else being equal – as the level of available resources decreases (i.e.as there is less to lose). 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 study period (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.[56] Although, allegedly, this result does not allow us to unequivocally pin down the mechanism, it suggests 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 with no political power.

[56]Table C.5, in Appendix C, shows that the result is confirmed whenever considering the simple interaction between RI_i^{power-} and the variable capturing ethnic-specific variations in rainfall expressed in SD (regression 5), whenever also all double and triple interaction terms for RI_i^{power+} are included in the same regression (regression 6), and whenever 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).

8 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 0.43 standard-deviations. The result is driven by rainfall during the growing season and is remarkably robust across a large set of placebo tests and robustness checks.

We also find power relationships across ethnic groups to play a significant role in the link between inequality and conflict. Combining the analysis at the country level and at the ethnicity level, we find that a more unequal distribution of rainfall is particularly prone to spur ethnic violence whenever an ethnic group with limited access to executive power is penalized with respect to the leading ethnic group. The effect is driven by groups that have no power at all and is strongest for groups that have recently lost their 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 ethnic groups excluded from power 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 of resource inequality we are able to circumvent the limitations that have affected previous empirical studies and to 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 clear evidence that the link between inequality and conflict strongly depends on the specific power relationships among the different ethnic groups.

Our findings suggest that measures should be taken to prevent that an increase in the variability of weather conditions, related for instance 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 the irrigation systems – has the potential to reduce ethnic conflict prevalence. Redistributive policies that provide compensation for areas penalized by the weather might also help reducing the risk of vi-

olence. On top of this, our results suggest 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 clear 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, the 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 to test the robustness of the findings presented here.

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Figure 1: Number of years of civil conflict by country

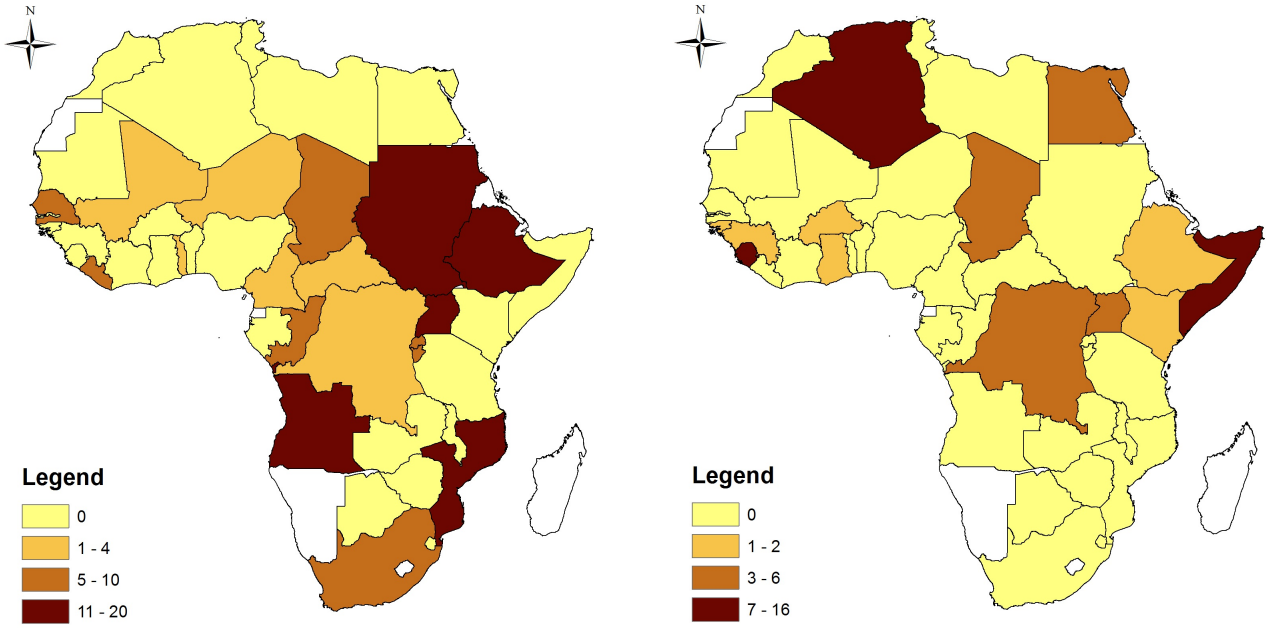
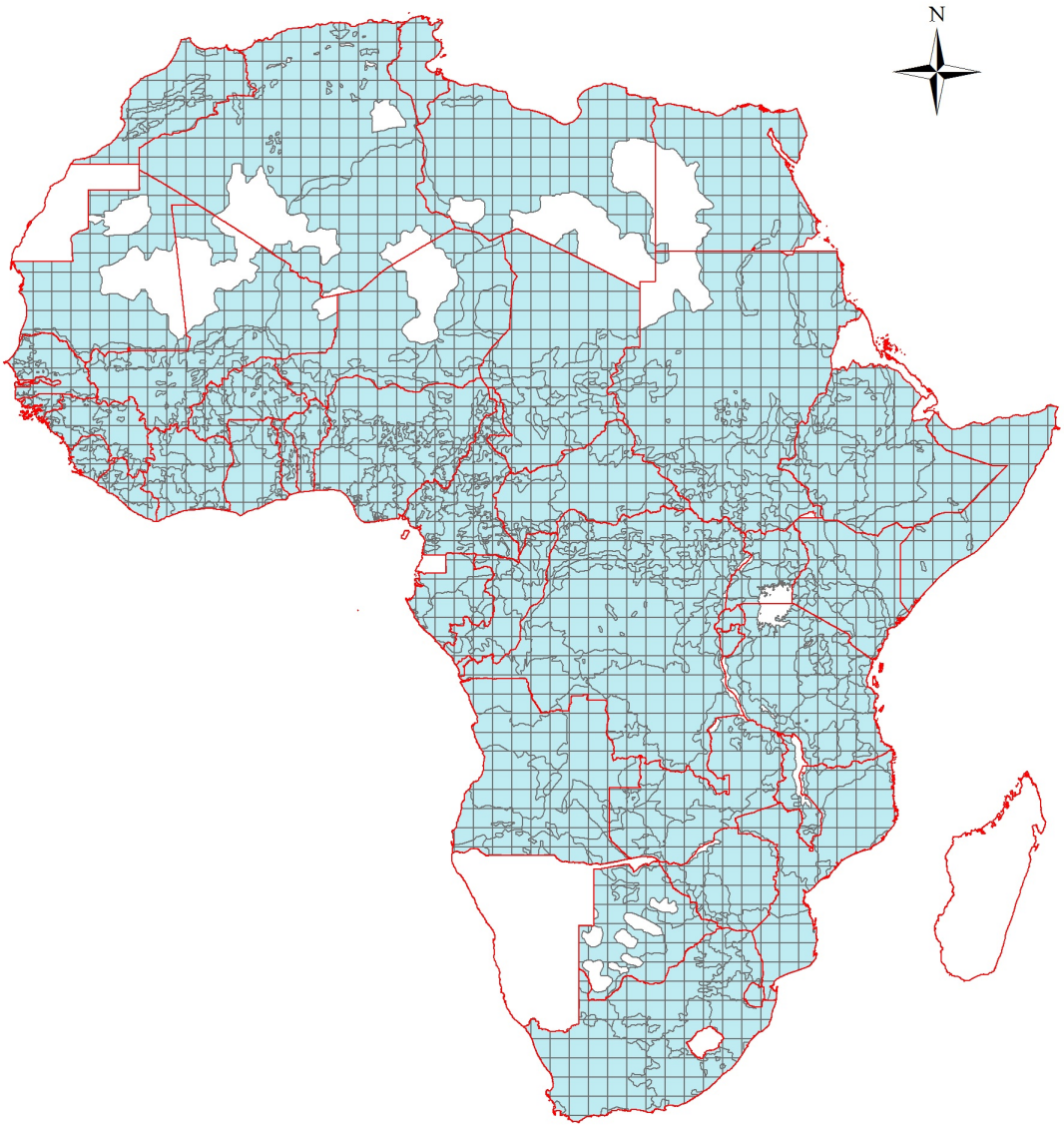


Fig. 1a: Ethnic Conflicts

Fig. 1b: Non-Ethnic Conflicts

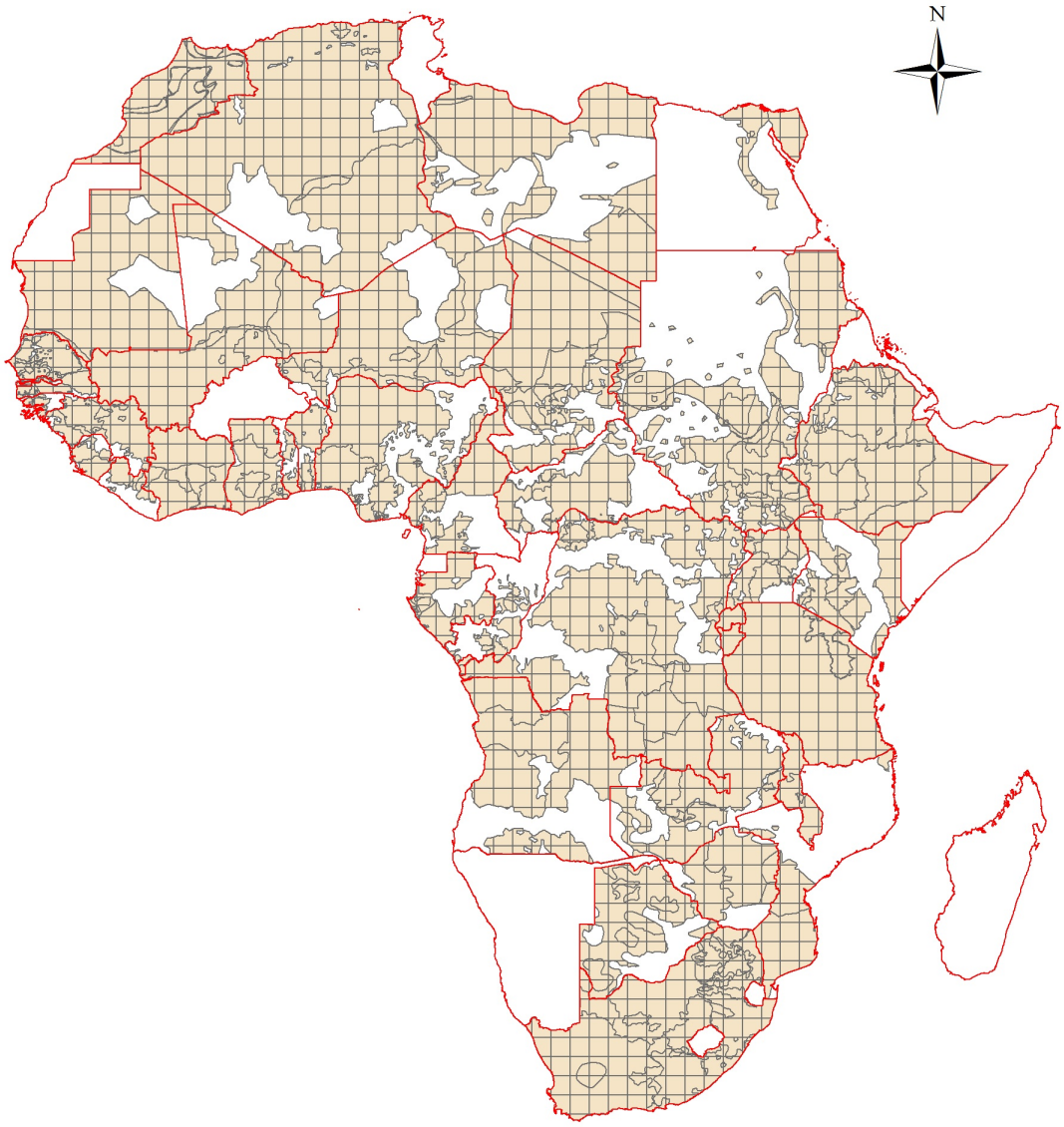
Notes: The two figures visually illustrates the number of years in which each country in the sample was involved in ethnic (Figure 1a) or non-ethnic (Figure 1b) civil conflicts, over the period 1982-2001. Information on the classification of the civil conflicts is taken from the Ethnic Armed Conflict (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 2: Dataset construction – GREG



Notes: The figure shows how the dataset has been constructed, by spatially merging three different maps: a grid of 1.25 $\times$ 1.25 degree cells, GREG map of ethnic homeland boundaries (gray lines), and African country borders (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.

Figure 3: Dataset construction – GeoEPR



Notes: The figure shows how the dataset has been constructed, by spatially merging three different data sources: a grid of 1.25 × 1.25 degree cells, yearly Georeferenced EPR (GeoEPR) maps of ethnic boundaries from 1982 until 2001 (gray lines), and African country borders (red lines). Areas in white are excluded from the analysis.

Table 1: List of Countries

	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 has 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 2: Summary Statistics

	Mean	Min	Max	Std.dev.	Obs
A. Conflict					
Civil Conflict	0.25	0.00	1.00	0.43	840
Ethnic Conflict	0.18	0.00	1.00	0.38	840
Ethnic Conflict Onset	0.04	0.00	1.00	0.20	721
B. Key Inequality Variables					
BGRI, growing season	0.23	0.00	1.00	0.23	840
WGRI, growing season	0.12	0.00	1.00	0.19	840
NRI, growing season	0.34	0.00	1.00	0.24	840
C. Other Inequality Variables					
BGNI	0.34	0.00	1.00	0.26	420
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, 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
D. 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
Avg rainfall, non-growing season	3.43	0.00	33.59	5.03	840
Rainfall growth, growing season	0.03	−0.70	2.90	0.31	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
GDP per capita (constant 2005 price), thousands	2.04	0.16	20.21	2.95	836
Population, millions	15.16	0.65	126.01	19.30	840
Openness, share	54.12	1.16	187.34	28.28	836
Individuals affected by natural disasters, thousands	243.38	0.00	23331.47	1258.18	840
Aid gross disboursements, USD millions	123.86	0.00	8497.34	343.37	840
Autocracy	0.53	0.00	1.00	0.50	840
Oil and Gas Gini	0.17	0.00	1.00	0.25	840
Years without ethnic conflicts	21.19	0.00	41.00	14.07	840
Avg temperature, growing season	23.47	15.20	28.53	2.91	840
Ethnic Conflict in neighboring countries, share	0.18	0.00	1.00	0.22	840
Autocracy in neighboring countries, avg	0.48	0.00	1.00	0.37	840

Notes: All inequality measures have been normalized by taking $(X - X_{min})/(X_{max} - X_{min})$. **BGRI** indicates Between-Group Rainfall Inequality. **WGRI** indicates Within-Group Rainfall Inequality. **NRI** indicates National Rainfall Inequality. **BGNI** indicates Between-Group Nightlight Inequality (only available for the years 1992-2002). **Adm units** indicates that the inequality measure has been computed considering level 1 administrative borders rather than ethnic homeland's boundaries. **SDs** indicates that the inequality measure has been computed comparing yearly deviations from each ethnic-group average rainfall, instead than comparing rainfall levels. **No cities** indicates that areas where (at least) one of the main cities is located have been excluded from the computation. **Temperature** indicates that the inequality measure refers to inequality in temperature, rather than in rainfall. The full sample include 42 countries over the period 1982-2001. For more details and sources, see the main text.

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. Production includes the quantities of the commodity sold in the market (marketed production) and the quantities consumed or used by the producers (auto-consumption). Production quantities of each commodity are weighted by 2004-2006 average international commodity prices and summed for each year. To obtain the index, the aggregate for a given year is divided by the average aggregate for the base period 2004-2006. 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 – i.e. the smaller of the two numbers of clusters. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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	5126	5126	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 – i.e. the smaller of the two numbers of clusters. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5: Main Effects

Dependent Variable:	Ethnic Conflict					
	(1)	(2)	(3)	(4)	(5)	(6)
BGRI, growing season	0.338*	0.706**	0.658**			0.957*
	(0.184)	(0.316)	(0.307)			(0.462)
BGRI, growing season (t-1)			0.482**			
			(0.195)			
BGRI, growing season (t-2)			0.446			
			(0.295)			
WGRI, growing season				−0.103		0.145
				(0.104)		(0.537)
NRI, growing season					0.290	−0.327
					(0.208)	(0.587)
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	0.04	0.70	0.71	0.70	0.70	0.70
N	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. **WGRI** indicates Within-Groups Rainfall Inequality. **NRI** indicates National Rainfall Inequality. 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 – i.e. the smaller of the two numbers of clusters. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 6: Falsification Tests

Dependent Variable:	Ethnic Conflict					Non-Ethnic
	(1)	(2)	(3)	(4)	(5)	(6)
BGRI, growing season	0.706**		0.734**		0.789**	−0.239
	(0.316)		(0.324)		(0.296)	(0.178)
BGRI, non-growing season		−0.130	−0.153			
		(0.134)	(0.130)			
BGRI, growing season, adm units				0.272	−0.084	
				(0.186)	(0.098)	
Country Effects	yes	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes	yes
Country Time Trends	yes	yes	yes	yes	yes	yes
R^2	0.70	0.70	0.70	0.70	0.70	0.66
N	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.Column (1) report the main result from Table 5. The BGRI index in column (2) only considers rainfall outside the growing season. The BGI index in column (3) and (4) considers level 1 administrative boundaries instead of ethnic boundaries for computing inequality. **Non-Ethnic Conflict** 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 – i.e. the smaller of the two numbers of clusters. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7: Robustness Checks I

Dependent Variable:	Ethnic Conflict						Onset
	Main	SDs	Polariz	Exclude Cities	Only SSA	Only variation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BGRI, growing season	0.706**		0.888**		0.803**	1.470**	0.523*
	(0.316)		(0.323)		(0.345)	(0.567)	(0.275)
BGRI, growing season, SDs		0.191**					
		(0.085)					
NRI, growing season			−0.129				
			(0.116)				
NRI × Polarization			−0.183				
			(0.292)				
BGRI, growing season, no cities				0.675**			
				(0.315)			
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	0.69	0.56	0.30
Countries	42	42	42	42	37	17	42
N	840	840	840	840	740	340	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. **NRI** indicates National Rainfall Inequality. Column (1) reports the main result from Table 5. The BGRI index in column (2) considers differences across ethnic groups in deviations from the group-specific average rainfall, instead of considering differences in rainfall levels. The polarization index used in column (3) is constructed following Montalvo and Reynal-Querol (2005). The BGRI index in column (4) does not consider areas that include capitals or other main African cities. Column (5) only includes 37 Sub-Sahara African countries. Column (6) only considers 17 countries for which there is variation in the dependent variable. **Ethnic Onset** is an indicator variable that takes on the value of 1 in the first year of an ethnic conflict and is missing for the consecutive years of conflict. 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 – i.e. the smaller of the two numbers of clusters. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 8: Robustness Checks II - Additional Controls

Dependent Variable:	Ethnic Conflict							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BGRI, growing season	0.635**	0.717**	0.710**	0.621*	0.697**	0.702**	0.710**	0.573*
	(0.288)	(0.309)	(0.324)	(0.303)	(0.306)	(0.322)	(0.285)	(0.275)
Ethnic Conflict (t-1)	0.312***						0.370***	0.338**
	(0.087)						(0.128)	(0.128)
BGI, growing season, temperature		0.370					0.402	0.468
		(0.627)					(0.355)	(0.369)
Malaria prevalence index			0.145				0.223**	0.264***
			(0.165)				(0.095)	(0.061)
Avg yearly rainfall along main roads (log)			0.024				0.044	0.063
			(0.068)				(0.093)	(0.110)
BGRI, growing season (t-1)				0.546**				0.303
				(0.227)				(0.198)
Rainfall growth, growing season				−0.029			−0.073**	0.013
				(0.031)			(0.032)	(0.059)
Rainfall growth, growing season (t-1)				−0.030			−0.062**	−0.054
				(0.031)			(0.026)	(0.034)
Additional Controls	no	no	no	no	yes	no	yes	yes
Neighbors Controls	no	no	no	no	no	yes	yes	yes
Lagged Controls	no	no	no	no	no	no	no	yes
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	0.73	0.70	0.70	0.70	0.71	0.70	0.74	0.75
N	840	840	840	840	836	840	836	835

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. The additional BGI index in column (2) considers inequality in temperature rather than in rainfall. *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, Oil and Gas Gini, (log) rainfall, (log) temperature. *Neighbor Controls* refers to the average autocracy indicator and the average prevalence of ethnic conflicts in neighboring countries. *Lagged Controls* refers to lags $t-1$ for all control variables defined before, with the only exception of *Years without ethnic conflicts*. We refer to the main text for a detailed definition of the single 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 – i.e. the smaller of the two numbers of clusters. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 9: Summary Statistics - EPR dataset

	Mean	Min	Max	Std.dev.	Obs
A. Country Level					
Ethnic Conflict	0.20	0.00	1.00	0.40	702
BGRI, growing season (EPR)	0.20	0.00	1.00	0.21	702
BGRI, non-growing season (EPR)	0.34	0.00	1.00	0.24	702
BGRI^{power}, growing season	0.14	0.00	1.00	0.18	702
BGRI^{size}, growing season	0.16	0.00	1.00	0.20	702
B. Ethnicity Level					
Ethnic Conflict	0.09	0.00	1.00	0.29	2995
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
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: Variables refer to analysis based on the EPR sample. ***Panel A*** 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** indicates Between-Group Rainfall Inequality. $\textbf{BGRI}^{power}$ indicates that the inequality measure has been 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*. $\textbf{BGRI}^{size}$ indicates that the inequality measure has been 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. ***Panel B*** includes all variables used for the analysis at the ethnicity level. $\textbf{RI}^{power}$ indicates rainfall inequality between the specific ethnic group and the *leading* group, normalized by the average rainfall in the country. $\textbf{RI}^{power+}$ ($\textbf{RI}^{power-}$) 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 variable that takes on the value of 1 when the ethnic group has been 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 as *Powerless* or below. The sample includes 172 ethnic groups, 37 countries and 20 years (1982-2001). Ethnic groups ruling alone – i.e. ranked as *Monopolist* or *Dominant* – are excluded from the analysis as they cannot be involved in any civil conflict against the central state, by definition. For more details and sources, see the main text.

Table 10: 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. $\textbf{BGRI}^{power}$ indicates that the inequality measure has been 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*. $\textbf{BGRI}^{size}$ indicates that the inequality measure has been 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 – i.e. the smaller of the two numbers of clusters. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 11: 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. $\mathbf{RI}^{power}$ indicates Rainfall Inequality between an ethnic group and the *leading* group, normalized by the average rainfall in the country. $\mathbf{RI}^{power+}$ ($\mathbf{RI}^{power-}$) 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 has been 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 as *Powerless* or below. **RainfallSD** records variation in rainfall during the growing season with respect to the ethnic-specific average over the study period (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 – i.e. the smaller of the two numbers of clusters. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix A - Data

In this appendix we describe more in details the data sources we have used for our analysis and the way we have built the variables. The structure mirrors the one 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

[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).

the institute of Ethnography at the USSR Academy of Science. Our dataset includes 214 different ethnicities, with an average of 11 (median is 10) different ethnicities per country (see Table 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.[3] 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*. 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.

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 cli-

[3] 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).

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

matic 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 ethnicity and administrative maps, as reported in Figures 2 and 3, in the main text.

cessed: 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.

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]

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

[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. autoconsumption). 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]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.

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 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 USD dollars, is taken from the Creditor Reporting System database kept by the OECD.[13] Information on *natu-*

[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 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*

ral 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]

Additional Reference in Appendix A

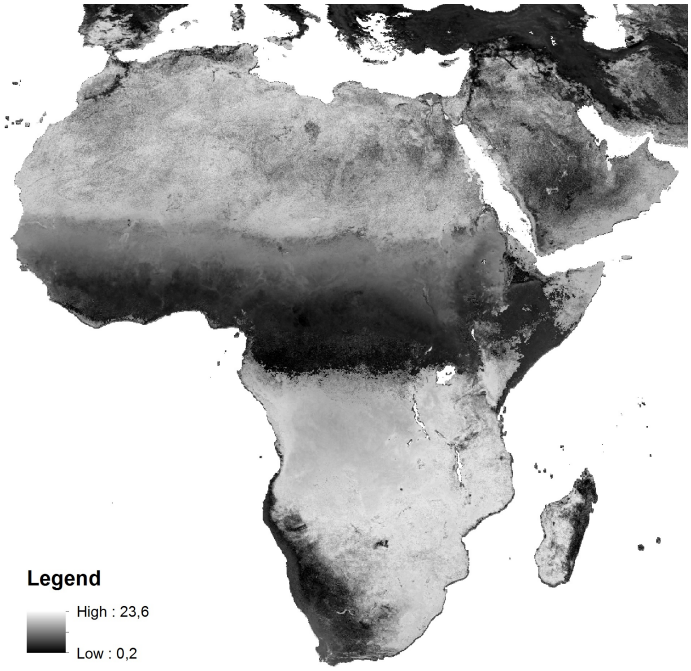
Stewart, F. 2002. Horizontal Inequalities: A Neglected Dimension of Development. *Queen Elizabeth House Working Paper Series 81*, University of Oxford.

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.

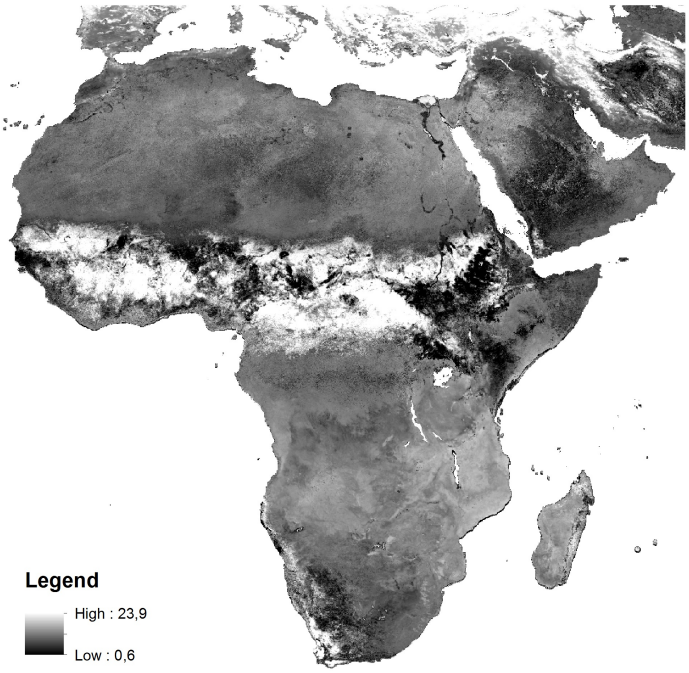
[15]Two different datasets are available for onshore and offshore fields. For our analysis, we focus on onshore fields. Data as well as explanatory material can be found at `https://www.prio.org/Data/Geographical-and-Resource-Datasets/Petroleum-Dataset/Petroleum-Dataset-v-12/` (Accessed: November 2015)

Figure A.1: Growing Season Start



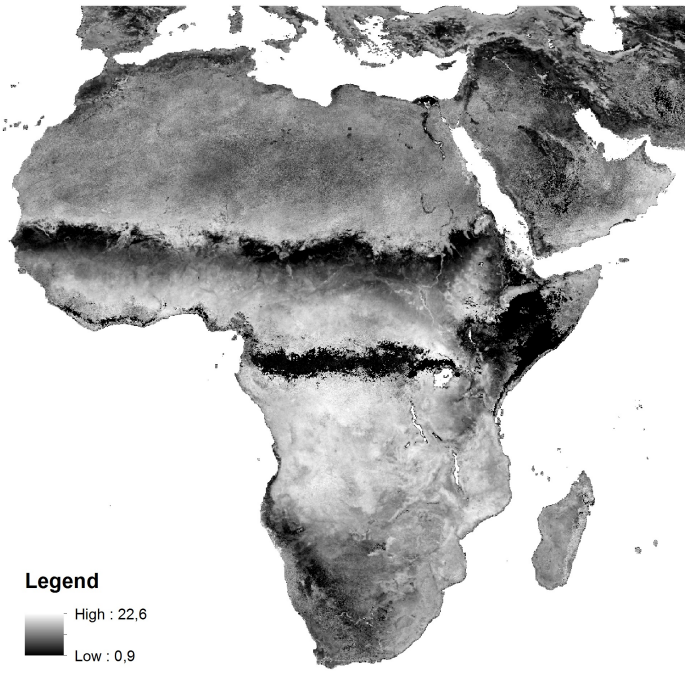
Notes: The figure shows the estimated start of the growing season for each 8 × 8 km pixel. The year is divided in 24 bi-weekly intervals and therefore the start date ranges from 0 to 24.

Figure A.2: Growing Season End



Notes: The figure shows the estimated end of the growing season for each 8 × 8 km pixel. The year is divided in 24 bi-weekly intervals and therefore the end date ranges from 0 to 24.

Figure A.3: Growing Season Length



Notes: The figure shows the estimated length of the growing season for each 8×8 km pixel. The year is divided in 24 bi-weekly intervals and therefore the length ranges from 0 to 24.

Appendix B - Figures

Figure B.1: Average and Standard-Deviation in BGRI

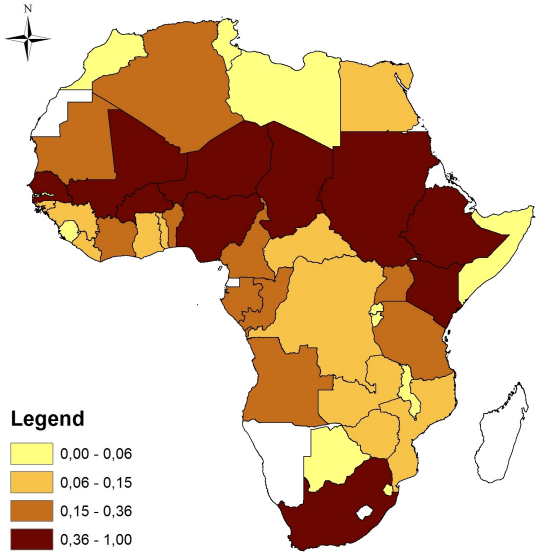


Fig. B.1a: BGRI Average

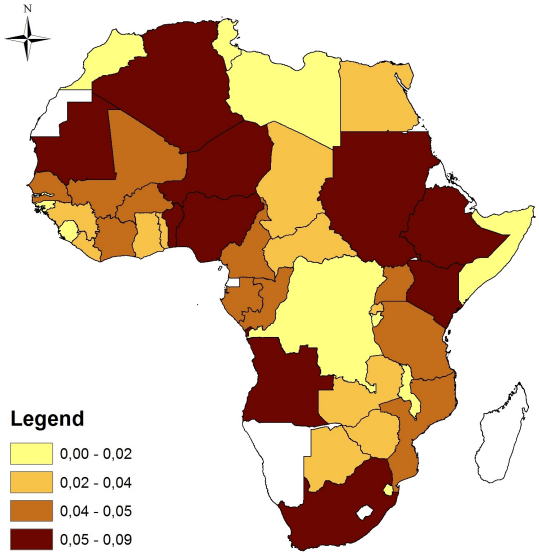


Fig. B.1b: BGRI Standard-Deviation

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.2: Average and Standard-Deviation in WGRI

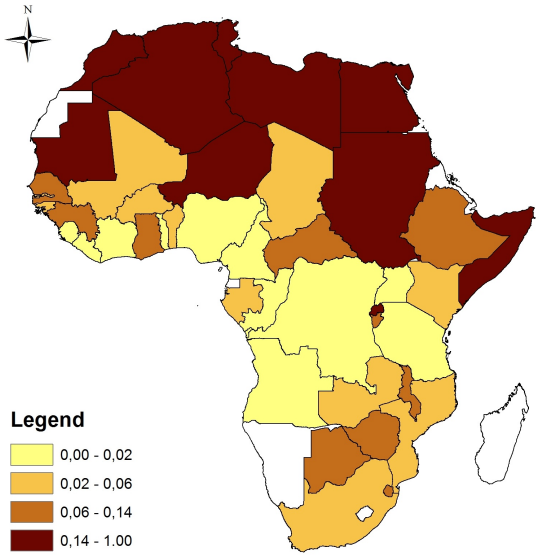


Fig. B.2a: WGRI Average

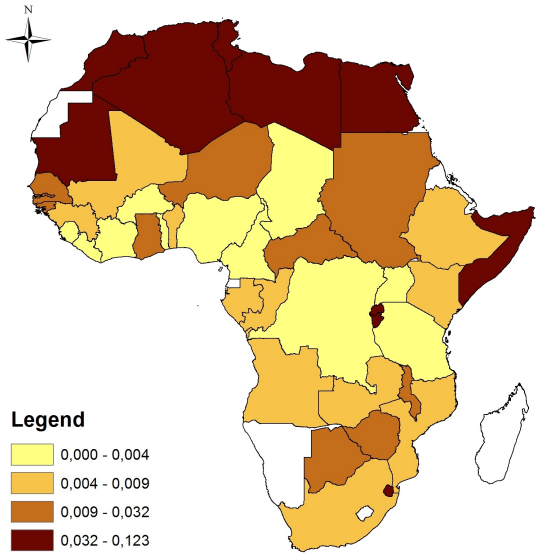


Fig. B.2b: WGRI Standard-Deviation

Notes: The figures illustrate the average (Figure B.2a) and standard-deviation (Figure B.2b) of Within-Group Rainfall Inequality (WGRI) over the period 1982-2001, by country. Different colors indicate different quartiles. Areas in white are excluded from the analysis.

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

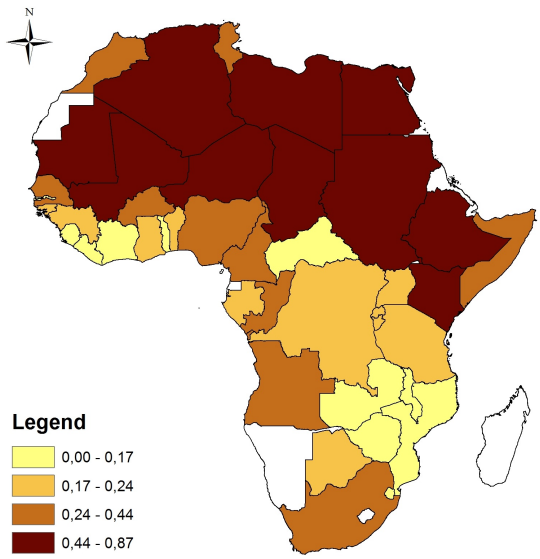


Fig. B.3a: NRI Average

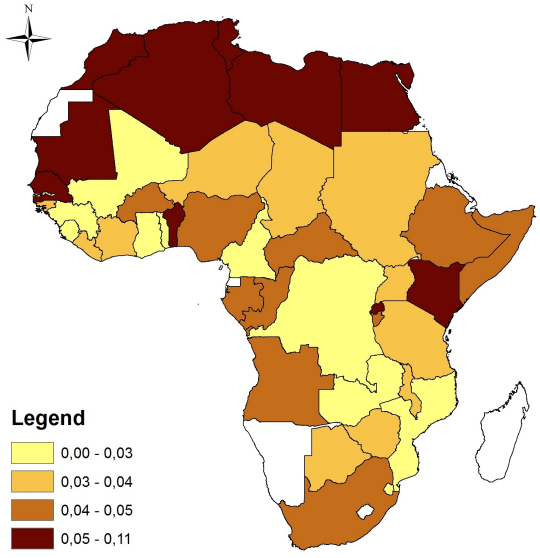
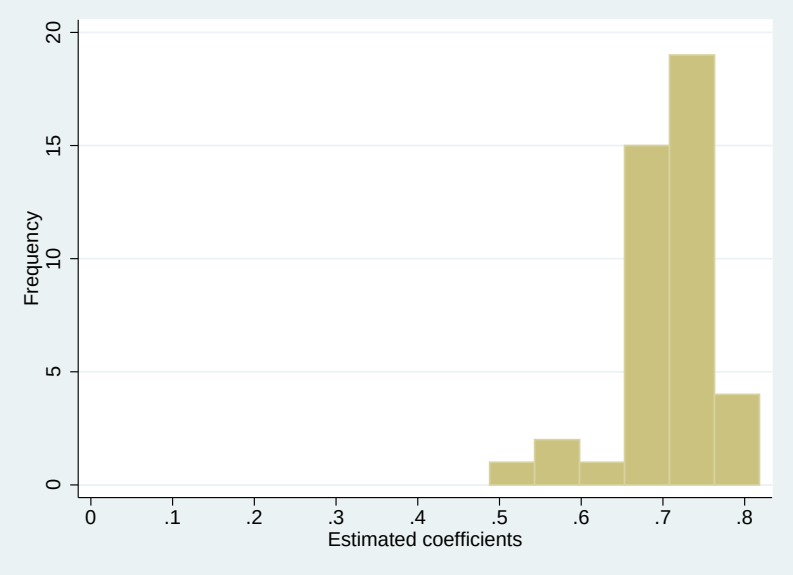


Fig. B.3b: NRI Standard-Deviation

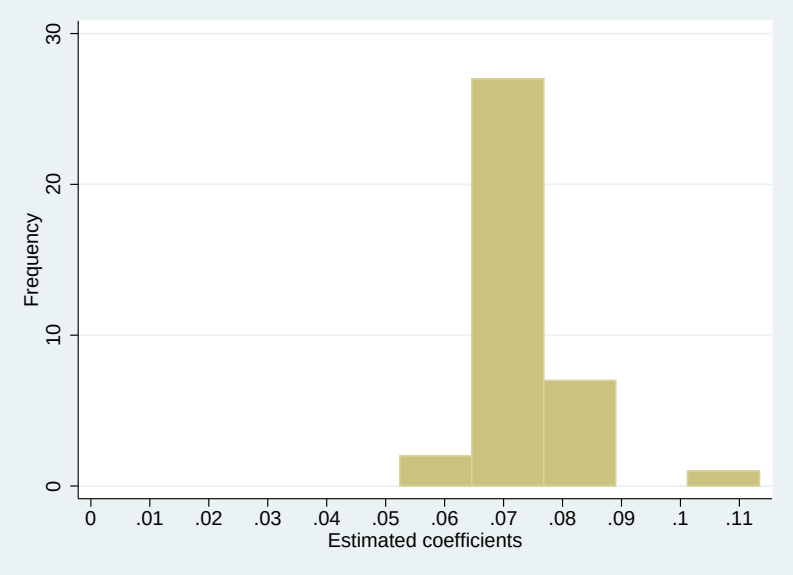
Notes: The figures illustrate the average (Figure B.3a) and standard-deviation (Figure B.3b) of National Rainfall Inequality (NRI) over the period 1982-2001, by country. Different colors indicate different quartiles. Areas in white are excluded from the analysis.

Figure B.4: BGRI estimates with different samples



Notes: The figure reports the coefficients on Between-Group Rainfall Inequality BGRI when dropping one country at a time in our main specification in column 2 of Table 5.

Figure B.5: 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 in our main specification in column 4 in Table 11.

Appendix C - Tables

Table C.1: List of Countries - GeoEPR

	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
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	12	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	13	3	0	9
LIBYAN ARAB JAMAHIRIYA	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	19	3	0	11
NIGERIA	20	0	0	27
RWANDA	20	10	0	2
SENEGAL	20	9	0	11
SIERRA LEONE	12	0	3	6
SOUTH AFRICA	20	7	0	13
SUDAN	20	19	0	30
TOGO	20	2	0	11
UGANDA	16	14	0	14
UNITED REPUBLIC OF TANZANIA	20	0	0	30
ZIMBABWE	10	0	0	10

Notes: The Table is similar to Table 1 and lists all countries included in the dynamic GeoEPR sample. For each country, the Table indicates the number of years (within the study period) in which the country has 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 and only records politically relevant ethnic groups. 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.2: 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. The BGI index referred to **Adm Units** considers level 1 administrative boundaries instead of ethnic boundaries for computing inequality. The BGRI index in **SDs** considers differences across ethnic groups in deviations from the group-specific average rainfall, instead of considering differences in rainfall levels. The index referred to **temperature** measures Between-Group Inequality in terms of temperature, rather than in rainfall. The specification **EPR** indicates that the measure is based on the GeoEPR dataset (rather than on the GREG one). **$BGRI^{power}$** indicates that the inequality measure has been 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 has been constructed with respect to the rainfall received by the ethnic group with the largest population.

Table C.3: Alternative specifications

Dependent Variable:	Ethnic Conflict						
Reference Table:	Table 5		Table 8				
Reference Regression in the Table:	3		1	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 5, when, respectively, the first (i.e. 1982) and first two (i.e. 1982 - 1983) years in the sample are excluded. Regression 3 replicates regression 1, from Table 8, 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 8, when the first year in the sample (i.e. 1982) is excluded. Regression 6 and regression 7 replicate (again) regression 4, from Table 8, 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 – i.e. the smaller of the two numbers of clusters. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.4: 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 $1 - (\sum_{i=1}^{E} r_i^2)$ where r 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 – i.e. the smaller of the two numbers of clusters. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.5: Ethnic Power Relations - Alternative specifications

Dependent Variable:	Rebel grup fighting in the name of the ethnic group						
"Downgraded" Specification:		*By 1 step*	*To no power*	*In 5 years*		*By 1 step*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RI^{power-}, growing season	0.092*	0.062**	0.062**	0.050	0.083**	0.064**	0.046
	(0.044)	(0.024)	(0.023)	(0.034)	(0.033)	(0.027)	(0.027)
RI^{power+}, growing season	0.002	0.011	0.011	0.010			
	(0.006)	(0.011)	(0.011)	(0.011)			
Oil share	0.153*						
	(0.073)						
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	yes	yes
Ethnicity Effects	yes	yes	yes	yes	yes	yes	yes
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	0.71	0.71	0.70	0.70	0.71	0.71
Ethnicities	80	172	172	172	172	172	172
Countries	16	37	37	37	37	37	37
N	1545	2995	2995	2995	2995	2995	2995

Note: This Table resembles the models and variables presented in Table 11 in the main text. Summary statistics for the new variables are reported in Table C.6. **Oil Share** indicates the share of the country's surface covered with oil and gas that falls within the ethnic group's territory. **Downgraded** is an indicator variable that takes on the value of 1 when the ethnic group has been downgraded in the power scale provided in the EPR dataset. The variable used in regressions 2, 6 and 7 is the same as the one considered in Table 11 and takes on the value of 1 if the group has been downgraded during the previous year. The variable used in regression 3 takes on the value of 1 only if the group has been 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 4 takes on the value of 1 if the group has been 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 study period. Regressions in column 6 and 7 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 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 – i.e. the smaller of the two numbers of clusters. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.6: 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(Rain$< \bar{r}_i$)	0.61	0.00	1.00	0.49	2995

Notes: Variables refer to analysis based on the EPR sample. **Oil Share** is built following Morelli and Rohner (2015) and indicates the share of the countryâs 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 has been 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 has been 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 has been 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 study period.