Ethnolinguistic diversity, elections and violent conflict in sub-Saharan Africa*

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Abstract

I study subnational ethnolinguistic diversity and violent non-state conflict in sub-Saharan Africa, and how this relationship varies over the electoral cycle. I construct measures of local-level diversity by combining georeferenced information on ethnolinguistic groups with population data of high spatial resolution. Ethnolinguistic fractionalization (ELF) is positively correlated with the frequency of violent conflict events, while polarization is not. The correlation is large; an increase in ELF of one standard deviation is associated with a 30 % increase in the number of years in conflict. Employing a continuous diff-in-diff setup, I show that the electoral cycle enhances the ELF-conflict relationship; event frequency increases with temporal proximity to presidential elections, but only where ELF is high. This effect is symmetric around elections, and is not likely due to pre-election government repression or post-election violence. I argue that the ethnically contentious nature of African presidential elections exacerbates the conflictual impact of existing divisions by making ethnic identities more salient. This finding suggests that efforts to reduce the importance of ethnicity in sub-Saharan African politics can mitigate conflict in the region.

Keywords: ethnolinguistic fractionalization; conflict; salience; africa; elections
JEL classification: D72; D74; Z13; O55

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1 Introduction

Ethnolinguistic diversity is believed to be one of the most important reasons for Africa's growth tragedy since the 1960s, when most states on the continent gained independence. Easterly and Levine (1997) provide empirical evidence for this, and argue that ethnolinguistic conflict is the cause of low growth. The evidence on the link between ethnolinguistic diversity and conflict, however, is mixed. The first generation of empirical papers were cross-country studies, and found either a positive or zero correlation between ethnolinguistic fractionalization or polarization, and conflict.[1] A second wave of research has been aimed at investigating the role of political exclusion of ethnic groups in sparking violent conflict, taking subnational variation into account. In general, the presence of excluded groups in a country is positively correlated with civil war, and the location of these groups also predicts the area in which fighting occurs.

The move to the subnational level is sensible, given that there is often severe within-country heterogeneity in ethnolinguistic diversity, and that conflict is frequently a subnational phenomenon. Yet, the recent tendency to exclusively focus on the political status of groups means that we have little knowledge about the role of pure diversity measures—such as ethnolinguistic fractionalization and polarization—below the country level. There is also little research into how the relationship between ethnolinguistic diversity and conflict varies over time. In particular, the role of ethnic identity and the salience of ethnicity in the context of conflict has largely been ignored in empirical studies.

Moreover, there is little evidence of how the choice of subnational geographical unit of aggregation matters for the study of conflict. For example, the potential for violent conflict outcomes likely depends on the distance between potential actors. Particular to the context of ethnic diversity, small geographical units will mechanically lead to low values of fractionalization, which may lead to an understatement of its effect on conflict. Moreover, the sign of the effect may depend on the degree to which groups have potential for daily interaction, which is more likely at a small geographical scale. At the same time, a too large geographical area containing geographically distant groups may not generate enough tension for violent conflict to materialize.

In this paper I revisit the evidence on ethnolinguistic diversity and conflict in a subnational context. First, I estimate the cross-sectional correlation between ethnolinguistic diversity and non-governmental conflict frequency at the subnational level, conditional on controls to account for confounding factors. Specifically, I include measures of his-

[1] Section 2 provides an overview.

torical conflict, geographical variability and malaria ecology, all factors that have been shown to have predictive power on current day ethnic diversity, and that also are correlated with conflict. I also examine whether the size of subnational observational units matters by systematically varying the level of geographical aggregation.

I construct subnational indices of the two most common measures of diversity, fractionalization and polarization, which I connect to event-based data on violent conflict where both actors are non-governmental groups. Ethnolinguistic fractionalization is positively correlated with conflict frequency. Correlations are larger and only statistically significant in subnational units at intermediate levels of geographical aggregation, providing some guidance for future research regarding the appropriate unit of analysis. The estimates are sizable; for example, in units of 220 by 220 km, an increase in the fractionalization index of one standard deviation is associated with a 30 % increase in the number of years with at least one conflict event. Using the methodology developed by Oster (forthcoming) to assess the importance of unobservable confounding factors, I estimate lower bounds for these coefficients that are well above zero, and still significant in magnitude. The correlation is also largely unaffected by controlling for the presence of politically excluded groups. Polarization is weakly negatively correlated with conflict in units of 440×440 km. However, if one of the conflict actors is a government, polarization is strongly positively correlated with event frequency.

Second, I exploit the ethnically contentious nature of sub-Saharan African politics to analyze how the diversity-conflict relationship changes over the electoral cycle. I find that both the likelihood and frequency of conflict increase around presidential elections in highly fractionalized areas. A back-of-the-envelope calculation suggests that as a country moves one year closer to an election, the number of conflict events in fractionalized areas increases by up to 30 %. On average, and disregarding fractionalization, countries are no more violent in the period around elections. Election months are also not more violent in other especially conflict prone areas, conditional on ethnolinguistic fractionalization. Oil, distance to border and the standard deviation of cultivable land are all strong predictors of conflict in a subnational cross section. Interacting them with the temporal proximity to presidential elections, only the distance to border displays a positive interaction effect, but this effect appears only in ethnically fractionalized areas.

These findings suggests that national efforts to reduce the ethnic component of election campaigns in sub-Saharan Africa can mitigate conflict, even if ethnolinguistic fractionalization stays fixed. The paper also sheds light on two aspects of the related literature. First, it helps explain the variability of results in the cross-country literature; aggregating at the country level masks relevant within country variation in both ethnolinguistic diversity and conflict. Second, while ethnopolitical dynamics are important, my findings suggest that non-political aspects of ethnic diversity have been incorrectly ignored as the conflict literature has moved to the subnational level.

2 Literature

2.1 Ethnolinguistic diversity and conflict

The evidence from cross-country studies on ethnolinguistic diversity and conflict is mixed. Most papers use ethnolinguistic fractionalization or polarization to measure diversity.[2] One of the first papers in this literature is Collier and Hoeffler (1998), who use ethnolinguistic fractionalization as a proxy for coordination costs. Costs are lowest when society is polarized into two equally sized factions, and highest when there is either a single group or many groups. In line with this prediction, they find that both the occurrence and duration of conflict is a concave quadratic function of ethnolinguistic fractionalization. Collier and Hoeffler (2004) distinguish between two categories of motives for civil war, "greed" and "grievances", of which the latter contains ethnolinguistic fractionalization. They find that "greed" in general has more predictive power than "grievances". In particular, ethnolinguistic fractionalization is positively but weakly correlated with conflict, and the results are sensitive the choice of model. In contrast, Fearon and Laitin (2003) find that ethnolinguistic fractionalization is *not* correlated with civil war, conditional income per capita. This holds even when looking at the subset of wars coded as "ethnic". In Hegre and Sambanis (2006), ethnolinguistic fractionalization is positively correlated with low intensity conflicts, but not with civil wars.

Montalvo and Reynal-Querol (2005b) criticize the use of fractionalization as the go-to measure of ethnolinguistic heterogeneity. They argue that measures of polarization like the ones in Esteban and Ray (1994) are closer to political and economic theories of conflict (e.g. Horowitz, 1985). The authors note that several influential papers (Easterly & Levine, 1997; Collier & Hoeffler, 1998; Collier, 2001) already implicitly base their theoretical foundations on a notion of polarization, but fail to align the empirics accordingly. In their empirical analysis Montalvo and Reynal-Querol (2005b) find that country-level polarization is positively correlated with conflict, while fractionalization is not. It should be noted, however, that most theories in this literature explicitly or

[2] Fractionalization measures the probability that two randomly drawn people belong to different ethnolinguistic groups, reaching a maximum when every individual belongs to their own group. Polarization is related, but is maximized when there are few, large groups. I define these concepts in more detail in section 3.1

implicitly analyze conflict over government control, like civil war. It is not clear whether polarization outperforms fractionalization for less severe conflicts that are not about national politics, and a few recent papers suggests that this may not be the case (Esteban & Ray, 2011; Mayoral & Ray, 2017).

2.2 Subnational evidence

Common to most of the research reviewed in section 2.1 is that it relies on cross-country data, or country panels with time variation in conflict. This is natural given the tendency of theoretical models to focus on contests between groups over public goods and government power; however, most intrastate conflicts are not country-wide, but rather fought within relatively limited geographical areas (Raleigh, Linke, Hegre, & Karlsen, 2010). Moreover, ethnolinguistic groups tend to be settled in specific geographic areas within countries, especially in sub-Saharan Africa. If a countries are fragmented at the national level, but different ethnolinguistic groups mostly live in separate regions, it is not obvious that they should start fighting. A cross-country analysis would conclude that ethnolinguistic diversity is uncorrelated with conflict, because it fails to account for within-country variation.

In the last decade, the empirical literature on ethnolinguistic groups and conflict has largely shifted to the subnational level. This development has been made possible by the production of high quality georeferenced data on both conflict events and ethnolinguistic groups. At the same time, there has been a movement away from pure diversity concepts like fractionalization and polarization. Wimmer, Cederman, and Min (2009) argue that these measures do not take into account ethnopolitical dynamics, and are therefore not relevant for conflict. Theisen, Holtermann, and Buhaug (2011) use a subnational grid-structure to assess the claim that marginalized ethnolinguistic groups in agrarian societies will fight more under severe droughts. They find that areas with excluded groups see more conflict, but droughts play no role in this. Fjelde and von Uexkull (2012), in contrast, show that the effect of rainfall anomalies on conflict is exacerbated by the presence of excluded groups. Basedau and Pierskalla (2014) investigate conflict in subnational regions of a) politically excluded groups and b) politically powerful groups, and find that conflict incidence is higher in both areas, relative to the rest of the country. A similar pattern is found in Asal, Findley, Piazza, and Walsh (2016).

2.3 Local ethnolinguistic fractionalization

A few studies have recently investigated subnational ethnolinguistic fractionalization, though not its effect on conflict. Montalvo and Reynal-Querol (2017) examine the extent to which the size of geographical units matter for the effect of ethnolinguistic fractionalization and growth, drawing on the cross-country analysis in Montalvo and Reynal-Querol (2005a). They find that fractionalization is good for growth in small units, but is irrelevant in large units. The proposed explanation is that ethnolinguistic specialization produces gains from trade, which boosts growth at the local level if groups coexist. In contrast, heterogeneous nations face difficulties in establishing good national institutions, which then eliminates the positive growth effect of trade at the local level. Desmet, Gomes, and Ortuño-Ortín (2016) explicitly contrast local and national levels of ethnolinguistic heterogeneity. They define a measure of local learning, which is the extent to which antagonism towards all individuals of a given group is affected by local mixing. Local learning is positively correlated with public provision of health, education and infrastructure. In contrast, national ethnolinguistic fractionalization has adverse effects on the same outcomes. One implication of these findings is that there a risk of making ecological fallacies when studying ethnolinguistic diversity.

As far as I am aware, subnational aspects of ethnolinguistic diversity and conflict have not been systematically investigated. Matuszeski and Schneider (2006) construct measures of geographic clustering of ethnolinguistic groups, analyzing country level conflict. They find that countries where groups are clustered tend to experience more civil war. This is related to the concept of local mixing, but they do not consider conflict at the subnational level. Ethnolinguistic fractionalization also enters as an interaction term or control variable in a few papers on natural resources and local conflict (e.g. Berman, Couttenier, Rohner, & Thoenig, 2017), but the fractionalization measure itself is always measured at the national level. The paper that comes closest to my analysis is Harari and La Ferrara (2017), who construct a measure of ELF at the cell level using the cell area share covered by ethnolinguistic groups. They find a positive correlation between ELF and conflict in areas of 110×110 km. However, their ethnicity data is based on the Atlas Narodov Mira, which contains substantially fewer ethnolinguistic groups than the Ethnologue data that I use. Furthermore, their method does not take into account group population, which mine does. They instead implicitly assume that groups are uniformly distributed across their homeland, and that different groups are equally populous in a given area.

2.4 Ethnic salience

Ethnic salience has largely been ignored in the literature on ethnicity and conflict. One exception is Bhavnani and Miodownik (2009), who find that allowing for variable (as opposed to fixed) ethnic salience has important implications for the link between ethnolinguistic polarization and conflict. There is also evidence documenting how elections affect salience and ethnolinguistic bias, although it is somewhat mixed. Hjort (2014) documents ethnolinguistic bias in ethnically mixed production teams in a plant in Kenya, and that the bias worsened during the post-election conflict in 2007–2008. Eifert, Miguel, and Posner (2010) show that self-reported ethnolinguistic identity is stronger around competitive elections in 10 sub-Saharan African countries. Michelitch (2015) documents an ethnolinguistic bias in taxi fares in Ghana, but this is not exacerbated during elections. In a lab experiment in Kenya, a highly ethnically divided country, Berge et al. (2015) fail to find evidence of ethnolinguistic bias, not even during elections. It is, however, unclear whether we can expect the latter two findings, which are based on surveys of individuals, to generalize to contexts in which stakes are higher, and where decisions are primarily made at the group level, such as with violent conflict between groups.

3 Conceptual framework

This paper seeks to answer two questions. First, is ethnolinguistic diversity in sub-Saharan Africa correlated with conflict at the subnational level? Second, does the electoral cycle modify this relationship, by causing variation in ethnic identity and salience? In this section I describe in detail why these questions are worth asking, and what I expect to find.

So far I have consistently used the term *ethnolinguistic* group, which suggests some form of linguistic classification of ethnic groups. Ethnic groups can be delineated along more than one dimension, but it is not obvious that all dimensions matter for the study of conflict. In Caselli and Coleman II (2013, Suppl. 1) observable markers are crucial in predicting conflict, because of the need to distinguish winners from losers in a way which makes it difficult for losers to pass as winners. Such markers may be language or physical features. Other classifications, such as religion, may also be relevant to conflict, but they are usually not fixed, even in the short run, meaning that individuals may be able to reclassify themselves. In practice, most empirical research employs some form of ethnolinguistic classification. First, language in itself may be an underlying cause of conflict, because it increases group cohesion and thereby coordination and potential for collective action. It is also a useful indicator because it correlates with other group features that may cause conflict. To be more precise, divergence of languages at some point in history is likely to be accompanied by geographical, religious and cultural divergence. Furthermore, sufficiently different languages makes it hard for members of one group to pass as members of another group. I continue to use the term *ethnolinguistic* in order to make the mode of group demarcation clear, except in contexts where the term *ethnic* is more appropriate. It is worth noting, however, that in the related literature these two concepts are often used interchangeably.

3.1 Ethnolinguistic fractionalization and polarization

The cross-country literature on the link between ethnolinguistic diversity and conflict has generally relied on two measures, fractionalization and polarization, and I include both in my subnational analysis. Ethnolinguistic fractionalization is equivalent to the Herfindahl index, and is computed with the following formula:

$$\text{ELF} = \sum_i s_i(1 - s_i) \ , \tag{1}$$

where s_i is the population share of group i. ELF is the probability that two individuals randomly selected from a given area belongs to two different groups.

For polarization, I employ the version in Reynal-Querol (2002), which differs from Esteban and Ray (1994) in that the distance between groups is dichotomous, 0 or 1, and that the weight on the own-group population share is 2, rather than a more general $1 + \alpha$. This parametrization is, however, consistent with all the axioms presented in Esteban and Ray (1994). The formula is:

$$\text{POL} = 4 \sum_i s_i^2(1 - s_i) \ , \tag{2}$$

While the relevance of polarization in the study of conflict has a solid theoretical foundation (beginning with Esteban & Ray, 1994), particularly at the country level, the grounds for considering fractionalization is often unclear. Esteban and Ray (2011) provide a rationale, however, showing that fractionalization may be relevant when the contested prize is private and rival.[3] The reason is that conflict over public goods directly taps into the distance between group preferences, because distance increases the cost of being imposed a suboptimal amount or mode of public goods. Since fractionalization ignores

[3] Esteban, Mayoral, and Ray (2012) provide matching empirical evidence.

group distance, it does not predict such conflicts well. For private contestable prizes, however, this effect is irrelevant, so what matters is the number of groups and their relative size. To the extent that rival goods are confined to specific geographic areas (e.g. point source natural resources), as opposed to public goods, a corollary of their model is that ethnolinguistic fractionalization within small areas may cause conflict.

Similarly, Mayoral and Ray (2017) theoretically and empirically study the role of group size in conflict, and find that small groups are more likely to fight over private goods, while large groups fight over public goods. This is consistent with Esteban and Ray (2011), in that ethnolinguistic fractionalization is high in the presence of many small groups, and vice versa for polarization. Buhaug (2006) argues that ethnolinguistic fractionalization matters because it affects the likelihood that any two groups will find it in their interest to engage in violence. He claims that fractionalization is especially relevant when the outcome is territorial conflict, and empirically confirms this prediction at the country level. Since territorial conflict is likely to be confined to specific geographic areas, we should expect to find a stronger correlation with fractionalization as the unit of analysis goes below the country level. In light of this discussion, the first hypothesis to be investigated is:

Hypothesis 1 *Subnational areas with high ethnolinguistic fractionalization are more likely to experience local conflict.*

The case for polarization is not clear at the subnational level, especially when conditioned on the level of fractionalization. The treatment of polarization in the literature implies that it is relevant when the contestable prize is public, like control over government and the provision of public goods (Esteban & Ray, 1994; Montalvo & Reynal-Querol, 2005b; Esteban & Ray, 2011; Horowitz, 1985). To the extent that both the contribution to and consumption of public goods may be confined within small geographical areas, for example in decentralized states, polarization may play a role in subnational conflict. However, it seems unlikely that central governments will allow groups to fight for control over local public goods, perhaps except in fragile states with little central control of the periphery. Although any particular theoretical prediction cannot be derived from the literature, a thorough investigation of subnational ethnic diversity would be incomplete without an analysis of polarization.

For both measures of diversity, I account for varying distance in terms of linguistic and cultural traits. Recent studies show that the linguistic distance between groups matters for conflict outcomes (Desmet, Ortuño-Ortín, & Wacziarg, 2012; Desmet et al., 2016; Esteban et al., 2012). In these papers, linguistic distance is measured by exploiting the separation of languages at different points in history. Since linguistic separation is partly a result of geographical distance between groups, we expect larger cultural and genetic differences between groups with languages that separated 100,000 years ago than those that separated 100 years ago. The operationalization of linguistic distance is discussed in section 4.2.4.

The literature does not provide any guidance about the size of the area in which ethnolinguistic diversity is relevant for conflict, and so I remain agnostic, *ex ante*. I want to avoid using administrative divisions, because they may be endogenous to both ethnolinguistic group settlement patterns and historical conflict. Similar to Montalvo and Reynal-Querol (2017), I instead explicitly analyze the role of geographical size of areas, by constructing grids of square cells covering the African continent, and varying the resolution. The set of cell sizes is 0.5, 1, 2, and 4 degrees latitude and longitude. For completeness I also provide estimates at the country level.

3.2 Presidential elections, ethnic identity and divisions

I do not have data on ethnic group settlement areas at different points in time, so I can only test hypothesis 1 in a cross-sectional setup. Granted, if the location of groups stays relatively fixed over time, we should not expect to much temporal variation in diversity anyway. However, even though fractionalization may be fixed, there are time-varying factors that determine its implications for various outcomes. One such factor is likely the electoral cycle. Politics is highly ethnically contentious in many sub-Saharan African countries, and ethnicity is an important instrument in electoral campaigns and political mobilization (Chabal & Daloz, 1999). There is also recent empirical evidence of ethnolinguistic favoritism in sub-Saharan African politics; Dickens (forthcoming) shows that when the ethnicity of the president changes, co-ethnics benefit economically. This implies that the stakes in ethnically centered elections are substantial, which likely reinforces any existing ethnic divide. Moreover, Eifert et al. (2010) provide evidence that elections strengthen ethnic identification. They use survey data from 10 sub-Saharan African countries to show that individuals identify more strongly with their ethnic group when surveyed closer to a competitive presidential election. They argue that politicians use the "ethnic card" in order to swing voters, and that elections enhance ethnic divisions because the electoral outcome will determine who gets to take part in the spoils of political office in the next presidential term. Hence, elections are likely to affect both the salience of group-level ethnic divisions, and individual-level ethnic identification. In the following I use *ethnic salience* as a collective term for these two concepts.

Theories of ethnic diversity and violence emphasize the importance of ethnic salience in enhancing group cohesion, solving barriers of collective action, and in enabling post-war division of the contested prize (Caselli & Coleman II, 2013, Suppl. 1). In line with this, I introduce the term *effective fractionalization*, which is salience-weighted fractionalization. For example, if people are either not aware of their ethnicity, or are not conscious about the existing ethnic divide, effective fractionalization is very low. However, it is not likely to fall to zero, because ethnic salience is always strictly positive when groups are defined in terms of language (if languages are sufficiently distinct). I interpret the electoral cycle as exogenous variation in effective fractionalization. In light of the above discussion, I set out to test the following hypothesis:[4]

Hypothesis 2 *Conflicts in ethnically fractionalized areas increase in frequency and intensity as a country gets closer to a presidential election.*

4 Data and methodology

4.1 Structure of data

Before presenting data sources and construction of variables, it is useful to be aware of how the data is structured. The data are from a variety of sources, and take the shape of either *points*, *lines* or *polygons*.[5] These are all matched to the unit of analysis by some geographical relationship (e.g. intersection or distance). The units of analysis are derived from geographical grids of four different resolutions, each containing contiguous square cells with sides of 0.5, 1, 2, and 4 degrees latitude and longitude.[6] The grids are superimposed on the African continent and intersected with national borders. This is done to guarantee that all cells only contain data that is relevant for the country it covers.[7] As I concentrate on sub-Saharan Africa, I exclude cells in Morocco, Algeria, Tunisia, Libya and Egypt. I also include a country-level structure to compare the results with the existing cross-country literature.

[4]Note that there is no systematic empirical evidence that election cycles in sub-Saharan Africa cause variation in conflict incidence, although anecdotes of post-election ethnic violence are easy to find (E.g Gettleman, 2008; Dixon, 2017).

[5]Polygon features are georeferenced two-dimensional objects, bounded by three or more connected line segments.

[6]1 degree latitude/longitude is approximately 110 km at the equator. At higher absolute latitudes, the kilometer value of one degree longitude is lower, and so cells are smaller. The largest 1 degree cell is about 12,300 km^2 and the smallest whole cell is 10,300 km^2.

[7]Cells of different sizes are perfectly aligned, so that there are always, respectively, 4, 16 and 64 cells of 0.5 degrees within the 1, 2, and 4 degree cells (except on borders).

4.2 Ethnolinguistic groups

4.2.1 Data sources

The ethnolinguistic diversity measures are based on two inputs: gridded population data, and polygons of language groups with information on group population within each country. I get population data for 1990 from the History Database of the Global Environment (HYDE).[8] It contains disaggregated estimates of population at a 5 arc minute resolution, which is 1/12th of a degree of latitude. I then take the sum of these population counts within each analysis unit. To ensure that results are not sensitive to the choice of population data, I also include sensitivity tests using data from UNEP and WorldPop. These sources only provide data starting in 2000, so I rely on HYDE in the main tables to minimize bias from a potential effect of conflict on population shares.

Data on language groups is from the World Languages Mapping System (WLMS), which provides the most comprehensive mapping of ethnolinguistic groups to date. It is a digitized version of the 17th edition of the Ethnologue, and contains information on the settlement areas of ethnolinguistic groups, country-group level population and the entire family tree for each language. The database contains 8,822 ethnolinguistic groups, of which 2,765 are in Africa. Since group and grid-cell population are from different sources and therefore do not add up to the same totals, the former is normalized to match the total grid-cell population within countries. The group population data is based on country censuses from different years (mostly 1990–2010), so they are only comparable within a given country.

Not all languages in the WLMS contain equally detailed information about the spatial extent of the groups. Out of 2,765 groups in Africa, 2,478 are located with polygon features, some of which overlap for different groups. The polygons are detailed and accurately drawn, so they enable me to confidently assess whether or not a given language is spoken in a particular grid cell. Of the remaining 287 groups, 95 have precise point features; 131 have point features defined as "widespread", which means that they are meant to cover the entire country; and 61 have approximate center points of areas that are too vaguely described in the Ethnologue to be precisely located. The point features are one-dimensional, whereas groups likely have a footprint in some vicinity around that point. To deal with this, I estimate the spatial extent of the points by converting them into circular polygons. I make the polygon size proportional to the respective group population, using each country's average population density as a normalizing factor. I deal with unknown and widespread languages by assigning them to a polygon identical to

[8] Detailed information about public data sources is given in Appendix A, Table A.1.

the country in which the point falls, assuming uniform population distribution.[9] When languages cross country borders I treat them as separate groups.[10]

4.2.2 Allocation of group populations

In order to calculate ethnolinguistic diversity at a subnational level I need information on cell-level population shares of ethnolinguistic groups. I estimate these shares by combining the gridded population data with information on the population and geographical footprint of ethnolinguistic groups.[11] To divide cell populations between groups I use an iterative proportional fitting procedure (IPFP), commonly used in statistics and also known as "raking" (See Bishop, Fienberg, & Holland, 1975).[12] In the present application, it takes three inputs: A vector of country-group populations, a vector of country-cell populations and a *seed* matrix. The seed matrix constitutes the initial guess for population distribution, and is constructed by the spatial intersection of group polygons and cells. The IPFP then allocates the country-group populations across cells so that the result is consistent with the population shares of groups at the country level, and at the same time preserves the spatial allocation of country population across cells.

The procedure is illustrated with a 3 group by 3 cell example in Figure 1, where the matrix represents a country. The spatial intersection between groups and cells gives a binary seed matrix, where each element gets a value of 1 if a group polygon intersects the cell, and 0 otherwise. Note that the seed matrix does not need to be consistent with either margin.[13] The shaded row represents the population of each group in the country, and the shaded column contains the cell populations.

The first iteration of the IPFP allocates the cell populations across groups according to their proportions in the seed matrix. Since the seed matrix is binary, in practice this means that population is split equally among the groups that intersect a given cell. The second iteration allocates group populations across cells according to their proportions in the matrix resulting from the first iteration. The algorithm iterates back and forth

[9]Unknown languages may not be widespread like this allocation assumes; however, the median population of the groups with unknown location is 1,640, so the potential resulting error is minuscule.

[10]This does not affect the results, because I always include country fixed effects.

[11]An alternative strategy is to use census population data (See Gershman & Rivera, 2016); however, complete census data is available only for a handful of sub-Saharan African countries, and usually only with geographic information at the region or district level. This makes it unsuitable for the analysis in the present paper.

[12]The method is used in a similar application in Desmet et al. (2016).

[13]To ensure convergence, and following Desmet et al. (2016), I replace zero values with 10^{-7}, which gives each country-group a small but strictly positive probability of populating all cells within that country.

between margins in this manner, until cell-group populations converge, with a unique solution for a given seed matrix.[14]

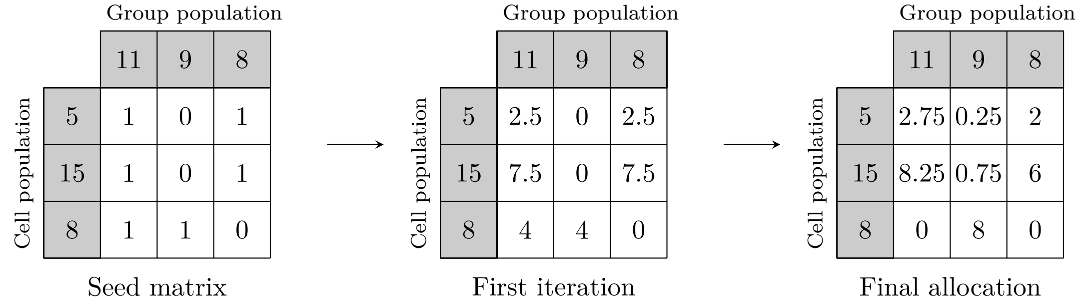


Figure 1: Iterative proportional fitting

4.2.3 Historical vs current settlement patterns

The WLMS polygons and population estimates are meant to reflect current settlement patterns. In this respect it differs from other commonly used data sources on the location of ethnolinguistic groups, like Murdock (1959) and the Atlas Narodov Mira (Bruk & Apenčenko, 1964), both of which can be regarded as documenting historical homelands, at least relative to current conflict. It is not obvious whether current or historical ethnolinguistic diversity is the appropriate variable when studying current conflicts.

On the one hand, if the link from diversity to conflict is a result of contemporary tensions, current settlement patterns are most relevant. In contrast, it may be that present day conflict is not directly related to current ethnolinguistic diversity, but instead a function of persistent historical ethnolinguistic tensions. In this case current settlement patterns are relevant to the extent that they are proxies for their historical counterpart. Gershman and Rivera (2016) provide evidence that inter-group migration is low, which suggests that the location of ethnolinguistic groups is stable over time, and that current diversity is good proxy for historical diversity. Of course, both historical and current diversity may be endogenous to historical conflict, and may otherwise be determined by factors that are correlated with present day conflict. I discuss this issue in section 4.4.

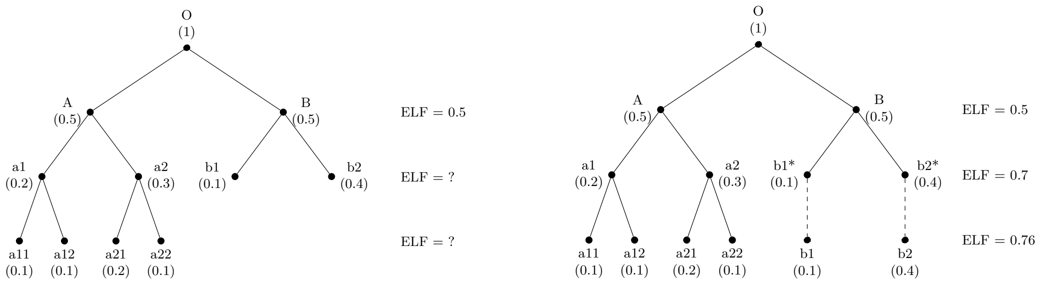
[14]Another way of allocating group populations to cells is to get a cell-group intersection, and then project the population data onto the resulting intersected polygons. This procedure is sub-optimal for at least two reasons. First, it relies heavily on the group polygon borders being very accurate. Second, when group polygons overlap, the researcher has little choice than to assume uniform distribution of population in the overlapping areas. This likely leads to less precision overall.

4.2.4 Linguistic distance

In order to account for the possibility that the linguistic distance between groups matters for conflict, I use information on genealogical relationship between languages, also from the Ethnologue. Specifically, I construct ELF and POL at all levels of the linguistic tree. This is not straightforward, because not all languages have the same number of ancestors. The median number of ancestors is 8, the minimum is 2, and the maximum is 12. This means that each level of the tree is not well defined from the outset. To see why, consider an area containing groups speaking Acholi and Songhai. Both are modern-day languages of the Nilo-Saharan family, but while Acholi has 8 ancestors, Songhai has only 1. Counting from the root of the tree, fractionalization at level 1 is 0, since they have the same initial ancestor. Fractionalization at level 2, however, would entail comparing the modern language Songhai with an ancient grandparent of Acholi. Fractionalization at level 8 is not defined, because Songhai only has 2 levels. To deal with this, I follow Desmet et al. (2012) in equalizing the number of ancestors by inserting artificial languages at each "missing" ancestral node between the current language and the nearest (grand)parent. The implicit assumption is that the Songhai language has gone through equally many stages of development as Acholi, although Songhai never experienced a split.

Figure 2 illustrates the procedure with a language tree in four levels, with population shares of each language in parentheses. The end node of each branch represents a current language. In Figure 2a, the languages a11, a12, a21 and a22 are all great-grandchildren of the ancestral language O, whereas b1 and b2 are grandchildren of O. It is not obvious how to calculate a measure like ELF at the third and fourth level of this tree. Figure 2b shows what the tree looks like after artificial languages b1* and b2* have been inserted. ELF is now well defined at each level.

In the baseline and most subsequent analyses, I use average fractionalization across each level of the tree. For example, if the tree in Figure 2b represents a grid cell, the ELF used in analyses will be $1/3 \cdot (0.5 + 0.7 + 0.76) = 0.65$. The rationale for this is that fractionalization in an area with sibling groups is intuitively different from fractionalization in areas with languages that are, say, fifth cousins. Sibling languages are likely often to be considered as different dialects, with members in practice belonging to the same ethnic group. By taking the average of ELF across all nodes I put more weight on fractionalization where groups are distant, while at the same time allowing for some diversity between more similar groups as well. Note, however, that overall geographical variation in average ELF will primarily be driven by levels farther from the root of the



(a) Original linguistic tree.

(b) Artificial languages b1* and b2* inserted at level 3.

Figure 2: Linguistic tree with artificial languages b1* and b2*

Notes: Figure adapted from Desmet et al. (2012).

tree, because the higher the aggregation, the more likely is it that groups are constant across space. Finally, I want to make clear that ELF closer to the root of the linguistic tree does not constitute a measure of *historical* diversity. This is because there is no information of historical group population sizes, and I cannot assume that population growth has been homogeneous enough to preserve the relative size of language groups over time.

4.3 Conflict

The conflict data is from the UCDP Georeferenced Event Dataset 5.0 (GED), which tracks conflict events across the world in space and time (Sundberg & Melander, 2013). The GED is based primarily on news sources. It is widely used in conflict research, and has a transparent and clearly defined methodology for coding events (See Croicu & Sundberg, 2015). There exists alternative data sources for geocoded conflict, notably the Armed Conflict Location and Event Dataset (ACLED) (Raleigh et al., 2010), but the GED covers a longer period (ACLED starts in 1997). The analysis in section 5.2.1 relies on wide temporal coverage to get sufficient variation in presidential elections, so I use the GED in all analyses.

Each observation in the GED represents a unique event related to a conflict with at least 25 battle deaths per year. A conflict may have many events, and the collection of events may be widely distributed in space and time. Version 5.0 of the GED records 27,072 events and 528 conflicts in sub-Saharan Africa in the period 1989–2015, although the final analysis dataset is a subset of this. First, I use only conflicts where neither side is identified as a government actor. These conflicts have a smaller geographical footprint[15] and are more likely to relate to local issues, hence they are better suited for analysis in small geographic units. Moreover, this paper does not concern political exclusion or government repression of single groups, which is likely more frequent in conflicts involving governments. This filtering reduces the dataset to 11,365 events in 448 conflicts.

Second, I keep only conflict events that are precisely located, coded with geographical precision 1 and 2 in the GED. Precision 1 signifies that an event has been geocoded to the exact location of a known, named point (town, hill, lake, etc.). Precision 2 represents an event that can be located within 25 km of a known, named point. This filtering excludes events that were only matched to administrative regions, long line features (e.g. rivers, borders), not clearly defined polygon features (e.g. informal regions), events tied only to the country as a whole, and events in international waters or airspace. The final dataset contains 8,473 unique events in 400 different conflicts. The distribution of events across years is shown in appendix Figure D.1.

4.4 Endogenous ethnic diversity

Disaggregated population estimates and the location of ethnolinguistic groups are not outcomes of a random process, so diversity may be endogenously determined. The most obvious causal identification strategies are not likely implementable. First, natural experiments are made difficult by the fact that the data contain only a modern snapshot of group locations. Time variation in diversity could be introduced by looking at changes in subnational borders, but is not clear how permeable administrative divisions would be relevant as an area within which diversity should affect conflict frequency. Second, while it is possible to identify relevant historical instrumental variables, they will rarely plausibly satisfy the exclusion restriction, due to the long time lag between instruments and outcomes (Casey & Klemp, 2016). I therefore rely on controlling for identifiable and observable confounding factors to mitigate endogeneity bias.

There are two immediate causes for omitted variables bias. The first is endogeneity caused by persistent, historical conflict, and the second is that historical and geographical factors that have shaped ethnic compositions may also affect present day conflict. Conflict does seem to be persistent over time (Besley & Marta Reynal-Querol, 2014), although it is not clear in which direction diversity would be affected. Historical conflict would reduce diversity if it results in either the obliteration, forced migration or assimi-

[15] Constructing convex hulls around all event points that belong to the same conflict in the UCDP GED I find that the average extent of conflicts that involve at least one government actor is four times larger than non-state conflicts.

lation of at least one group. In that case, the correlation between diversity and current conflict will be an downward biased. In my view, this is the most likely scenario, and is also corroborated by evidence on religious diversity at the national level (Fletcher & Iyigun, 2009). There is also the possibility that historical conflict caused initially similar groups to diverge linguistically, but not separate geographically.[16] If that is the case, modern-day diversity is higher than it would be without a history of conflict, which results in an upward bias to the relationship between diversity and conflict. It is hard to assess the plausibility of this, and there is as far as I know no evidence in line with such a story.

In order to minimize the risk of bias from persistent conflict, I include for each cell a flexible set of controls on historical conflict. Using data from Brecke (1999), georeferenced by Fenske and Kala (2017), I calculate the distance from the closest historical conflict in the period 1400–1900 as well as the number of such conflicts that took place in a given cell. Importantly, the data includes events involving Africans, and also some conflicts where Europeans played no role at all. This ensures that the data does not simply capture the behavior of colonizers and slave traders.

Three additional factors stand out as potential confounders. The first two are identified in Michalopoulos (2012), who finds that ethnic diversity is higher in areas with high variability in elevation and quality of agricultural land. Variable elevation is associated with high costs of migration and trade, leading to isolation of groups and separation of languages and culture. Variable quality in agricultural land leads to location specific human capital. Over time this leads to a decrease in migration benefits, because production skills are not immediately transferable within a given region. Both of these factors are likely also correlated with present day conflict, and may thus lead to bias if omitted. Variability in soil quality may induce conflict by causing group-level inequality in endowments, thereby constituting a motive for land grabbing. Variation in elevation is highly correlated with measures of terrain ruggedness, which have been found to positively correlate with conflict in subnational studies (E.g. Carter, Shaver, & Wright, 2017), the idea being that rough terrain provides places to hide for fighting groups. I construct control variables for these confounding factors by calculating the standard deviation of agricultural land quality and elevation, using data from Ramankutty, Foley, Norman, and McSweeney (2002) and Digital Elevation Model (DEM) data from the USGS, respectively. Note that the data for land quality has an initial geographical resolution of 0.5 degrees, so its standard deviation is only available for grid cells above that size.

The third factor is identified in Cervellati, Chiovelli, and Esposito (2017), who find

[16]Conflict may also have caused groups to not mix and therefore not converge linguistically.

that areas climatically suitable for malaria have higher diversity. Due to a lack of medical treatment, alternative strategies in the form of endogamism and thereby group isolation evolved as group-level protection from the disease. As more and more members of a given group develop immunity, within-group marriage further increases the probability that malaria immunity is passed on to the next generation. At the same time, Cervellati, Esposito, Sunde, and Valmori (2017) find that months climatically suitable for malaria vectors have more conflicts, but only where historical prevalence is low. They attribute this to the low degree of immunity in these areas. Consequently, historical malaria exposure should, if anything, correlate *negatively* with conflict in a cross-section. To control for malaria prevalence, I use the malaria ecology index constructed by Kiszewski et al. (2004), who use long-term climatological data to predict the average life span of malaria vectors in a given area, and maps this to grid cells of 0.5 degrees. Since the variation in this index is driven by climate rather than the quality of health facilities, it is likely exogenous to both conflict and ethnolinguistic diversity.

I also include a number of control variables to reduce residual variance and increase precision of estimates, using predictors of conflict that have been identified in the literature. Conflict is generally more frequent close to country borders and far from national capitals (Buhaug & Rød, 2006). I calculate the distance to capitals using data on populated places from Natural Earth, and distance to borders with data from the Seamless Digital Chart of the World.

Conflict is also more likely in areas that host lootable natural resources (Lujala, Gleditsch, & Gilmore, 2005; Lujala, Rød, & Thieme, 2007; Lujala, 2009, 2010), which I capture by including dummies for oil, secondary diamonds and gemstone deposits. Primary diamond deposits—for which extraction requires large-scale mining—are excluded because they are not easily lootable by fighting groups. The data on oil, diamonds and gemstones is from Lujala et al. (2007), Gilmore, Gleditsch, Lujala, and Rød (2005) and Lujala (2009), respectively. I also include cell area, which is mechanically correlated with both conflict and ELF, since larger cells are more likely to contain additional ethnic groups or conflict events.[17] Finally, I control for population, from the same source that was used to construct diversity measures (i.e. HYDE 1990 in the main tables).

4.5 Elections and monthly conflict data

I get elections data from the Varieties of Democracy dataset, version 7.1 (V-DEM) (Coppedge et al., 2016). V-DEM records around 400 indicators of democratic institutions

[17]Cell area varies more at higher resolutions, because a larger fraction of cells are split at borders.

and election systems, and contains a database of all elections between 1900 and 2016. I extract the exact date of presidential elections and match this with a monthly grid-cell panel. In cases where countries hold a second round of elections, I use the date for the first round. The definition of a presidential election in the V-DEM excludes parliamentary republics like South Africa, Botswana, Ethiopia, and I follow that distinction. Other sub-Saharan African countries that do not appear with presidential elections over the sample period include monarchies (Lesotho and Swaziland), autocracies (Equatorial Guinea) and one-party states (Eritrea). Although I use presidential elections in the baseline, following the claim in Eifert et al. (2010) that these should be particularly ethnically contentious, I also examine the effect of parliamentary elections. The conflict data is limited to 1989–2015, but I include election data outside to avoid censoring early and late in the period.[18] The remaining sample comprises 292 elections taking place between 1986 and 2016 in 38 countries. In addition to the election date, I collect information on vote shares of winnings candidates and runner-ups, expert assessments of whether a given election was de facto competitive, and the number of presidential elections since 1900.

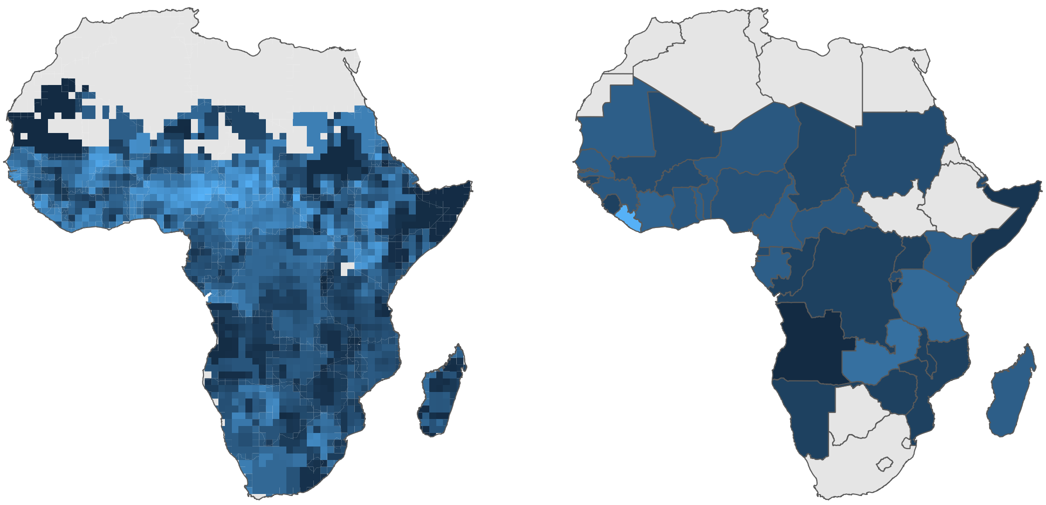
For each cell-month I calculate the number of months until the next presidential election, and the number of months since the previous election. I then construct a measure of election proximity, defined as the negative of min(*months until next election*, *months since previous election*). Hence, in theory, higher proximity can be interpreted as higher ethnic salience. I let the proximity measure be symmetric because Eifert et al. (2010) do not find evidence that the effects of proximity on salience are larger before or after the election. To measure monthly conflict frequency I complement the geographically matched UCDP GED conflicts with the exact date of each event, and calculate the number of events in a given cell-month. Some events span several days, in which case I use the start date. To complement the main conflict frequency measure, I also calculate the number of battle-related deaths in non-state conflict and the number of unique conflicts. The latter measure is increasing in the number of groups that are involved in fighting, whereas the number of events is an average of the intensity of each conflict and the number of fighting groups.

4.6 Sample

The maps in Figure 3 illustrate the final samples used in estimation. Figure 3a on the left shows the sample for the baseline cross-section regression on the 1 degree grid resolution.

[18] There are 11 countries in which the closest election to January 1989 was held in 1988 or earlier, and 11 countries that held an election in 2016.

The cells are colored according to the value of the ethnolinguistic fractionalization index, with lighter shades of blue indicating higher values. Sample inclusion is determined by WLMS polygon coverage; the white squares are missing from the sample because they contain no information on ethnolinguistic groups. The missing cells are primarily located in the Sahara, suggesting that the lack of data is due to sparse population. Figure 3b on the right shows the set of countries included in the analysis of presidential election proximity, with sample inclusion described in section 4.5. The different shades of blue represent the number of elections used in the estimation. The main source of variation here is the length of presidential terms.



(a) ELF at 1 degree

(b) Number of presidential elections

Figure 3: Sample maps

Notes: Lighter color shades in the Figure 3a represent higher values of ethnolinguistic fractionalization. Gray cells are excluded from the sample due to missing data on ethnolinguistic groups, or because the country is not part of sub-Saharan Africa. In Figure 3b the color shades represent the number of presidential elections per country. Countries in gray are either not part of sub-Saharan Africa or do not have presidential elections in the sample period.

5 Results

5.1 Ethnolinguistic diversity in a cross section

5.1.1 Empirical specification

To test hypothesis 1 on the link between ethnolinguistic fractionalization and conflict, I estimate the following equation

$$\text{conflict}_{ic} = \alpha_c + \delta \text{ELF}_{ic} + \beta \mathbf{X}_{ic} + \varepsilon_{ic} \ , \tag{3}$$

where conflict_{ic} is the share of years in the sample (1989–2015) where cell i in country c experienced at least one conflict event onset, and α_c is a country fixed effect. To repeat, ELF is the average fractionalization across all levels of the linguistic tree. $\mathbf{X}_{ic}$ is a vector of controls, and includes the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. In the country level analysis I drop all distance controls, because they are not well defined.

Unobserved conflict shocks in a given cell are probably not isolated within artificial grid cell borders, especially for the smallest grid resolutions, which means that error terms are not independent between units. To account for this, I allow ε_{ic} to be correlated within a cutoff radius of 650 kilometers, using the standard error estimator proposed by Conley (1999). Neighboring observations are weighted by a Bartlett kernel, which declines linearly with distance and is zero beyond the cutoff radius.[19] This particular cutoff is chosen in order to include all adjacent cells in the 4 degree grid.[20] Since I am considering intra-national conflict, I only allow for spatial correlation to occur within national borders. If cross-border correlation is (close to) zero, ignoring this will likely bias the standard errors downwards, since average spatial correlation in border cells will be too low.[21] For the same reason, I use robust standard errors in the country-level regressions.

[19]The Bartlett kernel is used for time-series in Newey and West (1987) and adapted to the two-dimensional spatial context in Conley (1999). The implementation of Conley (1999) standard errors in *R* is based on the "ConleySEs" function written by Darin Christensen and Thiemo Fetzer, available at https://github.com/darinchristensen/conley-se/.

[20]The results are robust to varying the cutoff, see Tables D.11 and D.12. Note, however, that a larger cutoff radius does not significantly affect the correlation structure anyway, since the immediate neighbors of a 4 degree cell will cover most countries entirely.

[21]Results are highly robust to allowing for cross-border correlation, see Table D.13.

5.1.2 Empirical results

Table 1: Ethnolinguistic fractionalization and non-state conflict

	Fraction of years with at least one event				
	0.5 deg.	1 deg.	2 deg.	4 deg.	Country
Ethnic fractionalization	0.004	0.020*	0.110***	0.240***	0.203
	(0.005)	(0.012)	(0.031)	(0.063)	(0.214)
Country fixed effects	Yes	Yes	Yes	Yes	No
Oster bounds (β^*)	0.003	0.016	0.086	0.135	0.186
Adj. R^2	0.240	0.315	0.438	0.547	0.444
N	7,457	2,304	796	314	44

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

Table 1 shows the result from OLS estimation of equation (3) for observation units of five different sizes.[22] First note that at the country level of aggregation the coefficient is positive at 0.16, but it is imprecisely estimated, and not close to statistically significant. This is consistent with evidence from the cross-country literature (Fearon & Laitin, 2003; Collier & Hoeffler, 2004). At 2 and 4 degrees the coefficients are positive, relatively large, and statistically significant at 1 %. The coefficients are also relatively large. For example, at 2 degrees, going from minimum (0) to maximum (1) fractionalization is associated with an 11 percentage point increase in the fraction of years with conflict events. The number of potential conflict years in 1989–2015 is 26, which implies that a cell with maximum fractionalization can expect almost three additional conflict years compared to a completely homogeneous cell. This is an increase of almost 160 % relative to the average number of years in conflict at 2 degrees (1.8), and 30 % for each standard deviation increase in ELF. The coefficient is about twice as high at 4 degrees, but the average number of years in conflict is correspondingly higher, at 2.9. At this resolution, going from 0 to 1 on the ELF index is associated with an increase in conflict years of 220 % compared to the overall average, and 45 % when ELF increases by one standard deviation.

The coefficients are closer to zero at 0.5 and 1 degrees, and the latter is statistically significant at 10 %. There are at least three possible explanations for this distinct

[22]See appendix Table D.18 for the coefficients on the control variables. Descriptive statistics for all variables used in the baseline analysis are presented in appendix Tables D.1–D.5.

drop in coefficients. The first is noisy measurement. If the ethnic group polygons are inaccurately drawn or the gridded population data are poorly estimated, there will be more noise in the ELF estimates in the smaller cells. In that case, the large drop in the coefficient that accompanies the decrease in cell size may be partly due to attenuation bias. Also, inaccuracies in the conflict event locations will lead to higher standard errors, especially in the 0.5 degree grids. (Recall that the location of conflict events are accurate to a distance of less than 25 km.) The second explanation is that the smallest grids are simply not relevant for studying the relationship between ethnic diversity and conflict, at least not for severe conflict events. One reason for this could be that groups avoid engaging in conflict close to their own settlements, to minimize civilian casualties and the destruction of infrastructure. This means that fighting efforts may be diverted away into neighboring cells, which will not be picked up in this specification. A third explanation is that ethnic fractionalization in small areas is correlated with the potential for local interaction between groups. If local interaction reduces conflict, these two effects may net each other out. I explore this possibility in Appendix B.

Even though I control for observable confounding factors, there is still a possibility that coefficients are biased by unobserved confounders, in which case the estimates in Table 1 will only partly, or not at all, reflect causal effects. In order to systematically assess the potential impact of remaining omitted variables, I estimate a lower bound of the causal effect by applying the methodology developed by Oster (forthcoming). The procedure draws on coefficient and R-squared movements from the inclusion of controls for observed confounders to estimate the likely bias arising from unobserved confounders.[23] In my implementation I assume that the bias from observed and unobserved confounders is of the same size, and that the theoretical maximum R-squared, R^2_{max}, is equal to $\min(1.3\tilde{R}^2, 1)$, where $\tilde{R}^2$ is the (non-adjusted) R-squared in the estimates of equation (3).[24] I denote the lower bound estimates by β^*, and the baseline coefficients by $\tilde{\beta}$. Country dummies are unlikely to be related to unobserved confounders, so to avoid including them in the estimation of β^* I center all variables on within-country averages. This assumption generally makes it a more demanding test, since country dummies have a large effect on R-squared.[25] Estimates of β^* are shown in Table 1, and at 2 and 4 degrees they are about 20 % and 50 % the size of the respective $\tilde{\beta}$'s. However,

[23] This procedure extends Altonji, Elder, and Taber (2005) by taking into account the effect of observable selection on R-squared. I estimate the lower bounds using the Stata module *psacalc* accompanying Oster (forthcoming), available at https://ideas.repec.org/c/boc/bocode/s457677.html.

[24] This threshold for R^2_{max} is recommended by Oster (forthcoming), and is the value at which 90 % of results from a sample of randomized trials survive the test.

[25] Empirically, the estimates of β^* when including country dummies in the control set is about 30 % higher than what I estimate in Table 1.

both of these lower bounds imply sizable causal effects, and satisfy the "survival" criteria suggested by Oster (forthcoming).[26]

I now add polarization to the equation. First note that, as is evident from Figure D.2 in Appendix D, there is a high correlation between ELF and POL in the lower part of the distribution. The regression estimates are displayed in Table 2. The coefficients on ELF are 30 % and 40 % higher in the 2 and 4 degree cells, respectively, compared to Table 1. This implies that the estimates in columns 3 and 4 of Table 1 are likely driven by variation in the upper part of the distribution, since the lower parts will be partialled out by the inclusion of POL.[27] The sign of the coefficient on polarization is not consistent between grid resolutions, but is negative, sizable and significant at 10 % for units of 4 degrees. Polarization is positively correlated with conflict at the country level, but the coefficient is imprecisely estimated, and not statistically significant. This is not unexpected, since the majority of theoretical treatments predict that polarization should be more important when the contested prize is public, e.g. government control, which non-state conflict likely does not capture.[28] Nonetheless, the conclusion from this exercise is that ethnic fractionalization is more relevant than polarization for explaining non-state conflict at the subnational level.

Table 2: Ethnolinguistic polarization

	Fraction of years with at least one event				
	0.5 deg.	1 deg.	2 deg.	4 deg.	Country
Ethnic fractionalization	-0.005	0.017	0.142^{***}	0.345^{***}	-0.022
	(0.010)	(0.025)	(0.047)	(0.082)	(0.287)
Ethnic polarization	0.008	0.003	-0.030	-0.113^{*}	0.335
	(0.008)	(0.021)	(0.044)	(0.072)	(0.258)
Country fixed effects	Yes	Yes	Yes	Yes	No
Adj. R^2	0.240	0.315	0.438	0.550	0.444
N	7,457	2,304	796	314	44

Notes: * p < 0.1; ** p < 0.05; *** p < 0.01. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

[26] "Survival" requires that $[\beta^*, \tilde{\beta}]$ excludes zero, and that β^* is within 2.8 standard errors of $\tilde{\beta}$.

[27] Splitting the sample by median ELF corroborates this result; ELF is strongly positively correlated in the above median sample, and not significantly so below the median. (See appendix Table D.6.)

[28] Indeed, in appendix Table D.8 I show that the signs of the coefficients on ELF and POL are flipped around when the outcome is state-conflict.

5.1.3 Robustness

In appendix section D.2 I present various robustness tests of the results in section 5.1.2. The qualitative conclusions from Table 1 are robust to alternative measures of conflict frequency, as well as intensity. In Table D.7 I present estimates for the 2 degrees analysis unit. Ethnolinguistic fractionalization is positively correlated in the same order of magnitude with the number of battle related deaths, the number of events, and the number of unique conflicts (which may contain several events). In the same table, I include estimates from regressions where I replace non-state with state conflict as the dependent variable. The fraction of years with state conflict is not significantly correlated with ethnolinguistic fractionalization. However, the number of events and unique conflicts display positive and significant coefficients. In Table D.8 I do the same exercise for polarization, now at 4 degrees, since this is where the coefficient on polarization was most precisely estimated. Polarization remains negative for all measures of non-state conflict, but turns positive for the fraction of years with state conflict, while the fractionalization coefficient turns negative, and both are highly statistically significant. This is partly expected, given theoretical predictions that polarization is the relevant diversity measure for explaining conflict over public goods (Esteban & Ray, 2011), in which the government is more likely to be involved.

In Appendix C I investigate the impact of spatial correlation. For example, diversity in neighboring cells may have implications for conflict in a given unit of observation, which implies that spatially lagged diversity is an omitted variable in (3).[29] Furthermore, conflict events in a given unit of observation are not likely to be spatially independent, and there is evidence of spatial spillovers in civil conflict (Harari & La Ferrara, 2017). If that is the case here, spatially lagged conflict is an omitted variable, and 1 will include biased estimates of the coefficient on ELF, even if spatially correlated disturbances are corrected with Conley (1999) standard errors. The results from regressions including spatial autoregressive terms and lagged independent variables is shown in Table C.1. The general lesson is that both spatial autocorrelation and lagged independent variables appear to be important in themselves, but they do not affect the direct within-cell correlation between ethnolinguistic fractionalization and conflict.

In order to investigate whether any particular country is driving the results, I re-estimate (3) while excluding countries one at a time, 44 regressions in total. Appendix Figure D.3 plots the ELF coefficients from these regressions, with 95 % confidence in-

[29]This corresponds to violation of the *stable unit treatment value assumption* first formulated by Rubin (1980).

tervals. None of the intervals contain zero, and the coefficient is generally stable across samples. The biggest drop occurs when I exclude Somalia, whereas the largest coefficient appears when Ethiopia is excluded. Table D.9 presents the numbers from these two regressions; the maximum and minimum coefficients are 0.13 and 0.07 at 2 degrees, and 0.25 and 0.17 at 4 degrees.[30] Table D.10 shows that results in Table 1 are robust to standard errors clustered at the country level. In Tables D.11 and D.12 I allow the cutoff radius for Conley (1999) standard errors to vary between 200 km and 950 km in 150 km intervals, with virtually no change to the estimates. In Table D.13 I relax the assumption of no cross-border correlation of disturbances, and the standard errors remain unchanged relative to Table 1.

When the unit of analysis is subnational and country fixed effects are included, large countries get more weight in the regression because they contain more cells, and thus more observations. In the country level analysis each country gets equal weight, so the coefficients may not be immediately comparable between the fourth and fifth columns of Table 1. At lower resolutions, the relative number of observations within large countries is approximately proportional to country area, but for small countries it is not, because the alignment of cells with respect to borders will vary between countries, and this matters more when there are fewer interior cells. For example, a country like the Gambia has a total area that is comparable to a single 1 degree grid cell, but since it intersects four cells it gets four observations. At 2 degrees, it intersects three cells, so it gets three observations, and thus increases its weight relative to a large country like Namibia, which has 93 and 3 cells at 1 and 2 degrees, respectively. In order to assess whether this matters for comparison across columns, I weight the regressions by country area. The results, presented in Table D.14, show that there is no substantial change to the relative size of coefficients.[31]

In Table D.15 I weight by cell population. Now all cell sizes from 0.5 to 4 degrees display a positive and highly significant coefficient. This may be a consequence of these regressions now placing more weight on cells where both ethnic fractionalization and conflict locations are more precise—the underlying data is likely measured with less error in highly populated areas—leading to less attenuation and imprecision overall. It may also be a result of ethnic conflict being an urban phenomenon. I test this possibility in Table D.16, where I add the interaction between ELF and population. The coefficient

[30] Somalia's southern region is ridden with clan based conflict. This corresponds well with my data; southern Somalia has a high degree of ethnolinguistic fractionalization, and also sees the majority of the country's conflict events.

[31] Due to the "ConleySEs" function not allowing for weighted regression, I use country clustered standard errors here.

on the interaction is positive, large and statistically significant in the 0.5 degree sample, but not otherwise. This indicates that a highly localized relationship between fractionalization and conflict only appears in areas with high population density. At higher levels of aggregation, the relationship appears unconditionally.

Finally, there is a worry that ethnic fractionalization is simply a proxy for the presence of excluded groups. The probability that at least one group is politically excluded generally increases with the number of groups in a given area. Hence, I may just be picking up an effect of political exclusion on conflict, which has already been documented in Asal et al. (2016), Fjelde and von Uexkull (2012) and Basedau and Pierskalla (2014). In Table D.17 I add an indicator for the presence of at least one politically excluded group, derived from the GeoEPR dataset (Vogt et al., 2015). The indicator is statistically significant at 4 degrees and at the country level. Importantly, however, the coefficients on ELF are largely unaffected.

5.2 Fractionalization and election proximity

5.2.1 Empirical specification

In now turn to the question of how the electoral cycle modifies the relationship between ethnolinguistic fractionalization and conflict. The results in section 5.1 provide evidence that more ethnically fractionalized areas in sub-Saharan Africa tend to experience conflict more often. Are these relationships altered by variation in election-induced ethnic salience at the intensive margin? As in the cross-sectional setup I exclude conflicts where one of the actors is a government. In this context, there is an additional rationale in that I want to exclude conflicts that relate to government intimidation of voters. Although interesting in itself, it does not fit well with the conceptual framework of this paper, in which elections exacerbate ethnolinguistic fractionalization, which in turn worsens the underlying tendency for conflict.

I test hypothesis 2 by estimating the following equation:

$$\text{conflict}_{ict} = \alpha_{ic} + \delta\left(\text{ELF}_{ic} \cdot \text{proximity}_{ct}\right) + \lambda_{ct} + \beta\left(\mathbf{X}_{ic} \cdot \text{proximity}_{ct}\right) + \varepsilon_{ict}\ , \qquad (4)$$

where conflict_{ict} is the number of unique non-state conflict events in a given cell and month. proximity_{ct} is the negative of the number of months to the closest presidential election. λ_{ct} is a country-month fixed effect, which picks up country specific monthly shocks to conflict, which additionally takes care of any seasonal patterns.[32] α_{ic} is a cell

[32]For example, there is evidence that conflict in agrarian societies is lower in harvest months (Cervel-

fixed effect, which together with λ_{ct} gives a continuous difference-in-differences interpretation of the parameter of interest, δ. $\mathbf{X}_{ic}$ is a vector of controls that includes the same variables as in equation (3) in the cross-section.

Shocks to conflict are likely to propagate both spatially and temporally. In order to make correct statistical inference on the estimate of δ, I allow the error term ε_{ict} to be correlated over time and across space. In particular, I employ spatial heteroskedasticity and autocorrelation consistent standard errors (spatial HAC), which was first used by Hsiang (2010), and then later in similar contexts by Harari and La Ferrara (2017) and Berman et al. (2017). The spatial HAC estimator is a combination of Conley (1999) and Newey and West (1987) standard errors, and ensures that inference is robust to contemporary correlation across cells in a surrounding neighborhood, and to correlation across time within a given cell.[33] I implement the spatial HAC standard errors with a distance cutoff of 650 km and time lag cutoff of 50 months, weighting both dimensions by a Bartlett kernel. The time lag cutoff corresponds to slightly more than four years, in effect allowing conflict shocks to be persistent from one election to the next, assuming an electoral cycle of four years.[34] The time-series for each cell is unique to the country, which corresponds to the inclusion of country-month fixed effects. As a result, spatial correlation is only permitted within country borders, which is reasonable given that the dependent variable is intra-national conflict.[35] In order to focus the discussion and presentation of results in this section, I focus on the 2 and 4 degree grid cell structures.

Causal identification relies on the assumption that ethnolinguistic fractionalization is exogenous to other factors that affect conflict frequency in the period around elections, and that election timing is exogenous to conflict events. The former is plausibly dealt with by the inclusion of $\mathbf{X}_{ic} \cdot \text{proximity}_{it}$ in equation (4), since the confounders discussed in 4.4 is equally relevant in this setting. The latter is likely to hold unconditionally, although in extreme cases it may be violated, for example if elections are postponed as a response to conflict or civil war; however, this will bias the estimates downward, since it induces a negative correlation between conflict events and election proximity.

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lati, Esposito, et al., 2017).

[33] I am not aware of estimators that allow for combination of spatial and serial correlation, in which shocks in one location affect error terms in a neighboring location in a subsequent period. However, I show in appendix Table E.6 that results are robust to clustering at the country level, which in practice is a spatial HAC with infinite cutoff values, in that it allows for errors in all cells within a country to be correlated across all periods.

[34] The average distance to an election is 24 months, which implies an electoral cycle of 48 months. The results are robust to varying both cutoffs.

[35] Results are robust to relaxing this assumption.

5.2.2 Empirical results

Table 3: Ethnolinguistic fractionalization and election proximity

	Number of non-state conflict events	
	2 deg.	4 deg.
ELF × proximity	0.0007*	0.0054***
	(0.0004)	(0.0015)
Cell fixed effects	Yes	Yes
Country-month fixed effects	Yes	Yes
Adj. R^2	0.1654	0.1581
N	215,784	86,184

Notes: * p < 0.1; ** p < 0.05; *** p < 0.01. Spatial HAC standard errors in parentheses with spatial cutoff at 650 km and temporal cutoff at 50 months. Controls include interactions of election proximity with the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, and population in 1990. All models estimated by OLS.

Table 3 shows the results from OLS estimation of (4).[36] Note that conflict events in a given cell-month are rare; in 4 degree cells there is on average one event every 17 months, so estimates are nominally small. The estimates indicate that the number of conflict events generally increase in ethnically fractionalized cells as countries get closer to the election. The coefficient at 4 degrees is almost ten times the size of the coefficient at 2 degrees, and three times the size when normalizing by average conflict frequency.[37] To put this in perspective, it is useful to back out the implied monthly increase in conflict frequency. For average (0.4) and max (0.8) ELF at 4 degrees, moving one month closer to an election leads to an increase in the number of events of about 3.5 % and 7 %, respectively (relative to the sample mean, 0.06). This is a moderate effect, although it roughly translates into 40 % and 85 % yearly increases, respectively, solely due to elections getting closer (ignoring serial correlation in conflict).

Equation (4) is in some sense a reduced form, where the hypothesized mediator is ethnic salience. I can use the results from Eifert et al. (2010) to get a ballpark estimate of the implied effect of ethnic salience on conflict. In Eifert et al. (2010), ethnic identification increases by 1.8 percentage points for each month closer to the election. This implies an elasticity of $3.5/1.8 = 1.9$, so an increase in ethnic identification of

[36] Descriptive statistics for variable with monthly variation are presented in appendix Tables E.2 and E.3.

[37] Average conflict frequency is trivially higher in larger cells.

50 % would lead to a doubling of the number of conflict events in a cell at average ELF. It should be noted that these back-of-the-envelope figures are rough estimates and should be interpreted with care, because conflict in subsequent months are likely not independent events, and there may be other ways in which elections affect conflict frequency than by enhancing effective ethnic fractionalization. Hence, this calculation likely overestimates the dynamic effect of election proximity through ethnic salience.

Appendix section E.3 contains tables with additional results. In Table E.4 I examine whether there is a general increase in conflict closer to elections, disregarding any interaction with fractionalization, and the short answer is "no". In Table E.5 I show that proximity to parliamentary elections has a positive effect on conflict, but this disappears once I include it together with presidential election proximity. Table E.7 shows that the interaction effect is strongest in the period within 18 months on each side of the election. Table E.8 shows that ELF $\times$ proximity has positive effects also on the number of deaths, conflict incidence and the number of unique conflicts, as well as different measures of government-involved conflict.[38] Table E.6 presents results from estimation of (4) with standard errors clustered at the country level. The coefficient at 2 degrees is now imprecisely estimated; however, this is a demanding test, as there are only 38 clusters, which is in the low end of the acceptable range and may cause standard errors to be overestimated. Finally, in Tables E.10–E.12 I present estimations of equation (4) where different sources of gridded population has been used in calculating the ELF index, with results virtually identical to Table 3.

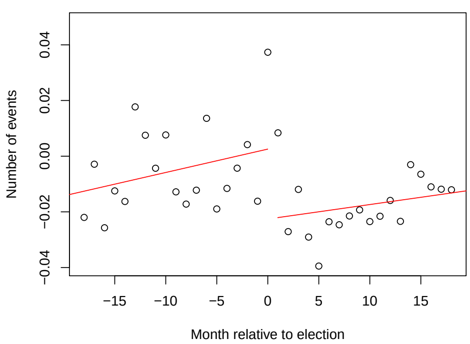
5.2.3 Voter intimidation and post-election violence

Equation (4) treats the months preceding and following an election in a symmetric way, an assumption which may be reasonably relaxed. For example, electoral campaigns may be instrumental in the mapping from election proximity to salience, in which case we might expect conflict to increase leading up to the election, and then decrease relatively quickly after votes are cast. Furthermore, post-election violence is not uncommon,[39] but it is likely more short-lived, and more related to protests over the outcome of the election than to changes in ethnic salience. If this is driving the results, we should expect a discontinuous increase in conflict right after the election month. A third possibility is that the incumbent government employs violence in the months leading up to the election in order to intimidate opposition groups, which suggests a sharp drop in events after the

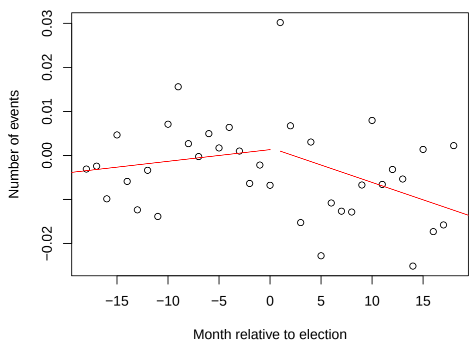
[38] See section 5.2.3 for a discussion of the implications of adding government violence to the outcome.
[39] See Duggan, Karimi, and Narayan (2017) for a recent example from Kenya.

election month. Given that I already filter out conflict events involving governments, this should be less likely; however, repression by proxy is a possibility (Eck, 2015).

In Figure 4 I plot the average number of conflict events within bins defined by monthly election proximity, with the actual election months in the zero-bin. The conflict events in Figure 4a on the left hand side includes a government actor, and Figure 4b includes only conflicts between non-governmental groups.[40] I restrict the data to cells with fractionalization above the 75th percentile, and conflict events inside a bandwidth of 18 months before and after the election.[41] Consistent with voter intimidation, state conflict increases steadily until it drops sharply right after the election. None-state conflict, however, displays a relatively symmetric (and apparently noisy) pattern over the 36 months included in this figure.



(a) State actor



(b) No state actors

Figure 4: Monthly average number of conflict events, ELF above the 75th percentile)

Notes: Data is restricted to cells with fractionalization above the 75th percentile, and conflict events inside a bandwidth of 18 months before and after the election.

To further investigate potential asymmetric effects I interact proximity$_{ct}$ with a dummy for the post-election period, which represents a formal test of the apparent pattern in Figure 4b. In order to get a "clean" distinction between pre- and post-election, I restrict the estimation sample to be within 18 months of an election. The results in Table 4 suggest that the effect of election proximity is indeed symmetric, as there is no significant positive or negative coefficient on the triple interaction.

[40]The two subsets of conflict data have no data points in common.

[41]Variation above median ELF seems to be relatively more important, as evident from Table D.6. In Table E.7 I show that results are stronger within 18 months of elections.

Table 4: ELF and presidential elections: split before/after

	Number of non-state conflict events	
	2 deg.	4 deg.
ELF × proximity	0.0061***	0.0125*
	(0.0023)	(0.0065)
ELF × proximity × post-election	0.0016	0.0072
	(0.0019)	(0.0055)
Cell fixed effects	Yes	Yes
Country-month fixed effects	Yes	Yes
Adj. R^2	0.1482	0.1909
N	98,915	39,986

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Spatial HAC standard errors in parentheses with spatial cutoff at 650 km and temporal cutoff at 50 months. Controls include interactions of election proximity with the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, and population in 1990. All models estimated by OLS.

5.2.4 Alternative interpretations

There are other possible reasons for why countries may see spikes in conflict and violent events closer to elections. For instance, differences in political preferences may become more visible, or supporters of different political parties may use violence to limit turnout in strategic areas. However, in appendix Table E.4 I show there is no general increase in conflict around elections, and most of such alternative mechanisms would already be picked up by the country-month fixed effects in Table 3. One possible threat to interpretation is that ethnically fractionalized areas are more conflict prone in general. Hence, election-induced spikes in conflict might be spatially distributed accordingly, but only because these areas are more susceptible to violence in the first place. If this is the case, I should be able to find a similar interaction effect for other conflict-prone areas, conditional on ethnolinguistic fractionalization.

To test for this, I turn the attention to interactions of election proximity with three other predictors of conflict: distance to capital, the standard deviation of soil quality, and a dummy for oil deposits. These are the controls that are consistently and significantly correlated with conflict in 2 and 4 degree cells (see appendix Table D.18).[42] Note that these interactions are already included as controls in Table 3,[43] but I display them here

[42]Population is likely trivially correlated with conflict, so I do not consider that as a relevant interaction.

[43]Their coefficients are reported in Table E.9.

for convenience. If there is a general spike in conflicts closer to elections that accrues to ethnically fractionalized areas simply because they are more prone to conflict, we would expect to see the same in other conflict-prone areas as well. The first two columns of Table 5 bring to bear some evidence for such an explanation. The interactions are non-significant for both oil and soil quality, but the distance to capital interaction is positively correlated with conflict frequency, and the coefficient is significant at 1 %.

In the last two columns, I include the triple interaction, ELF × proximity × distance to capital. This modifies the interpretation slightly, as the effect from the distance to capital interaction seems to accrue entirely to areas that are also highly ethnically fractionalized. Equivalently, the original ELF × proximity interaction effect only appears at a distance away from capitals. This result may be explained by a model in which the ability of governments to keep a lid on violent ethnic conflict is strongest near the center of their power, and weaker farther into the periphery. This finding is consistent with the results in Buhaug and Rød (2006), who find that territorial conflict is more likely far from capitals. If such conflicts are instigated by ethnically motivated secessionist movements, it is not surprising that ethnic fractionalization has a particularly strong link with conflict in the periphery.

Table 5: Election proximity interacted with other correlates of conflict

	Number of non-state conflict events			
	2 deg.	4 deg.	2 deg.	4 deg.
ELF × proximity	0.0007*	0.0054***	−0.0012**	0.0002
	(0.0004)	(0.0015)	(0.0006)	(0.0024)
Oil × proximity	0.0901	−0.3700	−0.1286	−0.5901
	(0.1324)	(0.4913)	(0.1458)	(0.4457)
Soil quality std.dev. × proximity	0.0013	0.0006	0.0015	0.0015
	(0.0013)	(0.0023)	(0.0013)	(0.0024)
Distance to capital × proximity			−0.3917	−0.8941
			(0.2747)	(1.2478)
Distance to capital × proximity × ELF			2.4256***	5.6970**
			(0.7747)	(2.7281)
Cell fixed effects	Yes	Yes	Yes	Yes
Country-month fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.1654	0.1581	0.1656	0.1584
N	215,784	86,184	215,784	86,184

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Spatial HAC standard errors in parentheses with spatial cutoff at 650 km and temporal cutoff at 50 months. The results are from Table E.9, and only modified with additional interactions in columns 3–4. All models estimated by OLS. The coefficients on oil and distance to capital are multiplied by 1,000 in order to improve presentation.

6 Conclusion

This paper has provided evidence for the role of ethnolinguistic diversity in explaining within-country variation in non-state conflict, and how this relationship is affected by temporal proximity to presidential elections in sub-Saharan Africa. So far, the literature has been concerned with country-level aspects of ethnic diversity, or the location of politically excluded groups within countries, and there is no evidence on time-variation in diversity.

Applying an iterative proportional fitting procedure to gridded population data at a resolution of 5 arc minutes, I estimate subnational ethnic group population shares and use this to construct indices of fractionalization and polarization at the local level. The appropriate subnational level for studying violent conflict is unknown *ex ante*, and partly an empirical question. I therefore run the analysis at various levels of geographical aggregation in order to retrieve the most relevant unit of analysis.

This paper provides two novel contributions. First, I show that ethnolinguistic fractionalization is positively correlated with the frequency of non-state conflict events at the subnational level, over and above the correlation with politically excluded groups. This implies that non-political aspects of ethnic diversity have been incorrectly ignored by the literature on subnational conflict. The correlation is most pronounced when variables are aggregated to grid cells of 2 and 4 degrees, which corresponds to squares of approximately 220 by 220 and 440 by 440 kilometers. In contrast, ethnic polarization is not important for subnational variation in non-state conflict, but it is highly positively correlated with conflict that involves a government actor. Together, these results help explain the variability of results in the cross-country literature; aggregating at the country level masks relevant within country variation in both ethnolinguistic heterogeneity and conflict.

Second, I present evidence that the electoral cycle affects "effective fractionalization", in which fractionalization is modified by the level of ethnic salience. Using the temporal proximity of presidential elections to get variation in ethnic salience, I find that conflict is significantly more prevalent in ethnically fractionalized areas when the election comes closer. Further investigation reveals that this effect is most pronounced within a semi-narrow band of 18 months before and after the election. There are no indications that the effect is driven by post-election violence or pre-election voter intimidation, and it appears only for presidential elections, and not for parliamentary elections. There is no country-wide increase in violence around elections, only in ethnically fractionalized areas. Elections also have an effect on conflict in areas far away from national capitals, but this accrues entirely to areas that are also highly ethnically fractionalized. Overall, this result suggests that national efforts to reduce the ethnic component of election campaigns in sub-Saharan Africa can mitigate conflict, even if ethnolinguistic fractionalization stays fixed.

References

Allport, G. W. (1954). *The Nature of Prejudice*. Reading, MA: Addison-Wesley.

Altonji, J. G., Elder, T. E., & Taber, C. R. (2005). Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *Journal of Political Economy*, *113*, 151–184.

Anselin, L. & Bera, A. K. (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In A. Ullah & D. Giles (Eds.), *Handbook of Applied Economic Statistics* (pp. 237–290). New York, NY: Dekker.

Asal, V., Findley, M., Piazza, J. A., & Walsh, J. I. (2016). Political Exclusion, Oil, and Ethnic Armed Conflict. *Journal of Conflict Resolution*, *60*(8), 1343–1367.

Baker, P. E. (1934). Negro-White Adjustment in America. *The Journal of Negro Education*, *3*(2), 194–204.

Basedau, M. & Pierskalla, J. H. (2014). How Ethnicity Conditions the Effect of Oil and Gas on Civil Conflict: A Spatial Analysis of Africa from 1990 to 2010. *Political Geography*, *38*, 1–11.

Berge, L. I. O., Bjorvatn, K., Galle, S., Miguel, E., Posner, D. N., Tungodden, B., & Zhang, K. (2015). *How Strong are Ethnic Preferences?* (NBER Working Paper No. 21715). The National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w21715

Berman, N., Couttenier, M., Rohner, D., & Thoenig, M. (2017). This Mine Is Mine! How Minerals Fuel Conflicts in Africa. *American Economic Review*, *107*(6), 1564–1610.

Besley, T. & Marta Reynal-Querol. (2014). The Legacy of Historical Conflict: Evidence from Africa. *American Political Science Review*, *108*(2).

Bhavnani, R. & Miodownik, D. (2009). Ethnic Polarization, Ethnic Salience, and Civil War. *Journal of Conflict Resolution*, *53*(1), 30–49.

Bishop, Y. M. M., Fienberg, S. E., & Holland, P. W. (1975). *Discrete Multivariate Analysis: Theory and Practice*. Cambridge, MA: MIT Press.

Bivand, R. & Piras, G. (2015). Comparing Implementations of Estimation Methods for Spatial Econometrics. *Journal of Statistical Software*, *63*(18), 1–36.

Blumer, H. (1958). Race Prejudice as a Sense of Group Position. *The Pacific Sociological Review*, *1*(1), 3–7.

Brecke, P. (1999). *Violent Conflicts 1400 A.D. to the Present in Different Regions of the World*. Data set.

Bruk, S. I. & Apenčenko, V. S. (1964). *Atlas Narodov Mira*. Glavnoe upravlenie geodezii i kartografii Gosudarstvennogo geologičeskogo komiteta SSSR. Institut ėtnografii im. NN Miklucho-Maklaja Akademii nauk SSSR.

Buhaug, H. (2006). Relative Capability and Rebel Objective in Civil War. *Journal of Peace Research*, *43*(6), 691–708.

Buhaug, H. & Rød, J. K. (2006). Local Determinants of African Civil Wars, 1970–2001. *Political Geography*, *25*(3), 315–335.

Carter, D. B., Shaver, A. C., & Wright, A. L. (2017). *Places to Hide: Terrain, Ethnicity, and Civil War*. Unpublished manuscript. Retrieved April 12, 2017, from https://www.austinlwright.com/civil-war/

Caselli, F. & Coleman II, W. J. (2013). On the Theory of Ethnic Conflict. *Journal of the European Economic Association*, *11*.

Casey, G. & Klemp, M. (2016). *Instrumental Variables in the Long Run* (MPRA Paper No. 68696). University of Munich. Retrieved December 8, 2017, from https://ideas.repec.org/p/pra/mprapa/68696.html

Cervellati, M., Chiovelli, G., & Esposito, E. (2017). *Ancestral Exposure to Malaria and the Emergence and Persistence of Ethnic Diversity in Africa*. Unpublished manuscript. Retrieved December 4, 2017, from https://sites.google.com/site/gchiovelli/

Cervellati, M., Esposito, E., Sunde, U., & Valmori, S. (2017). *Malaria Risk and Civil Violence* (CESifo Working Paper Series No. 6413). CESifo Group Munich. Retrieved from https://ideas.repec.org/p/ces/ceswps/_6413.html

Chabal, P. & Daloz, J.-P. (1999). *Africa Works: Disorder as Political Instrument*. African issues. Oxford, UK: Currey.

Collier, P. (2001). Implications of Ethnic Diversity. *Economic Policy*, *16*(32), 129–166.

Collier, P. & Hoeffler, A. (1998). On Economic Causes of Civil War. *Oxford Economic Papers*, *50*(4), 563–573.

Collier, P. & Hoeffler, A. (2004). Greed and Grievance in Civil War. *Oxford Economic Papers*, *56*(4), 563–595.

Conley, T. (1999). GMM Estimation with Cross Sectional Dependence. *Journal of Econometrics*, *92*(1), 1–45.

Coppedge, M., Gerring, J., Lindberg, S. I., Skaaning, S.-E., Teorell, J., Altman, D., Bernhard, M., Fish, M. S., Glynn, A., Hicken, A., Knutsen, C. H., Marquardt, K., McMann, K., Miri, F., Paxton, P., Pemstein, D., Staton, J., Tzelgov, E., Wang, Y.-t., & Zimmerman, B. (2016). *V-Dem Country-Date Dataset v6.2*. Varieties of Democracy (V-Dem) Project. Retrieved from https://www.v-dem.net/en/data/data-version-6-2

Croicu, M. & Sundberg, R. (2015). UCDP GED Codebook Version 2.0.

Desmet, K., Gomes, J., & Ortuño-Ortín, I. (2016). *The Geography of Linguistic Diversity and the Provision of Public Goods* (CESifo Working Paper No. 6238). Center for Economic Studies & Ifo Institute. Retrieved from https://ideas.repec.org/p/ces/ceswps/_6238.html

Desmet, K., Ortuño-Ortín, I., & Wacziarg, R. (2012). The Political Economy of Linguistic Cleavages. *Journal of Development Economics*, *97*(2), 322–338.

Dickens, A. (Forthcoming). Ethnolinguistic Favoritism in African Politics. *American Economic Journal: Applied Economics*. Retrieved December 8, 2017, from https://www.aeaweb.org/articles?id=10.1257/app.20160066&&from=f

Dixon, R. (2017). Clashes and violence continue after Kenya's disputed repeat presidential election. *Los Angeles Times: Africa*. Retrieved November 9, 2017, from http://www.latimes.com/world/africa/la-fg-kenya-election-clashes-20171027-story.html

Duggan, B., Karimi, F., & Narayan, C. (2017). 24 killed in post-election violence in Kenya, group says. *CNN*. Retrieved October 12, 2017, from http://www.cnn.com/2017/08/12/africa/kenya-elections-protests/index.html

Easterly, W. & Levine, R. (1997). Africa's Growth Tragedy: Policies and Ethnic Divisions. *Quarterly Journal of Economics*, *112*(4), 1203–1250.

Eck, K. (2015). Repression by Proxy: How Military Purges and Insurgency Impact the Delegation of Coercion. *Journal of Conflict Resolution*, *59*(5), 924–946.

Eifert, B., Miguel, E., & Posner, D. N. (2010). Political Competition and Ethnic Identification in Africa. *American Journal of Political Science*, *54*(2), 494–510.

Esteban, J., Mayoral, L., & Ray, D. (2012). Ethnicity and Conflict: An Empirical Study. *American Economic Review*, *102*(4), 1310–1342.

Esteban, J. & Ray, D. (1994). On the Measurement of Polarization. *Econometrica*, *62*(4), 819–851.

Esteban, J. & Ray, D. (2011). Linking Conflict to Inequality and Polarization. *American Economic Review*, *101*(4), 1345–1374.

Fearon, J. & Laitin, D. (2003). Ethnicity, Insurgency, and Civil War. *American Political Science Review*, *97*(1), 75–90.

Fenske, J. & Kala, N. (2017). 1807: Economic Shocks, Conflict and the Slave Trade. *Journal of Development Economics*, *126*, 66–76.

Fjelde, H. & von Uexkull, N. (2012). Climate Triggers: Rainfall Anomalies, Vulnerability and Communal Conflict in Sub-Saharan Africa. *Political Geography*, *31*(7), 444–453.

Fletcher, E. K. & Iyigun, M. (2009). *Cultures, Clashes and Peace* (IZA Discussion Paper No. 4116). Institute for the Study of Labor. Retrieved from https://EconPapers.repec.org/RePEc:iza:izadps:dp4116

Gershman, B. & Rivera, D. (2016). *Subnational diversity in Sub-Saharan Africa: Insights from a new dataset.* Unpublished manuscript. Retrieved December 4, 2017, from https://papers.ssrn.com/abstract=2851565

Gettleman, J. (2008). Ethnic Violence in Rift Valley Is Tearing Kenya Apart. *The New York Times: Africa.* Retrieved October 3, 2017, from https://www.nytimes.com/2008/01/27/world/africa/27kenya.html

Gilmore, E., Gleditsch, N. P., Lujala, P., & Rød, J. K. (2005). Conflict Diamonds: A New Dataset. *Conflict Management and Peace Science*, *22*(3), 257–272.

Harari, M. & La Ferrara, E. (2017). *Conflict, Climate and Cells: A Disaggregated Analysis.* Unpublished manuscript. Retrieved December 4, 2017, from https://real-estate.wharton.upenn.edu/profile/harari/

Hegre, H. & Sambanis, N. (2006). Sensitivity Analysis of Empirical Results on Civil War Onset. *Journal of Conflict Resolution*, *50*(4), 508–535.

Hjort, J. (2014). Ethnic Divisions and Production in Firms. *The Quarterly Journal of Economics*, *129*(4), 1899–1946.

Horowitz, D. L. (1985). *Ethnic Groups in Conflict.* Berkeley, CA: University of California Press.

Hsiang, S. M. (2010). Temperatures and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(35), 15367–15372.

Kiszewski, A., Mellinger, A., Spielman, A., Malaney, P., Sachs, S. E., & Sachs, J. (2004). A Global Index Representing the Stability of Malaria Transmission. *American Journal of Tropical Medicine and Hygiene*, *70*(5), 486–498.

Lujala, P. (2009). Deadly Combat over Natural Resources: Gems, Petroleum, Drugs, and the Severity of Armed Civil Conflict. *Journal of Conflict Resolution*, *53*(1), 50–71.

Lujala, P. (2010). The spoils of nature: Armed civil conflict and rebel access to natural resources. *Journal of Peace Research*, *47*(1), 15–28.

Lujala, P., Gleditsch, N. P., & Gilmore, E. (2005). A Diamond Curse?: Civil War and a Lootable Resource. *Journal of Conflict Resolution*, *49*(4), 538–562.

Lujala, P., Rød, J. K., & Thieme, N. (2007). Fighting over Oil: Introducing a New Dataset. *Conflict Management and Peace Science*, *24*(3), 239–256.

Matuszeski, J. & Schneider, F. (2006). *Patterns of Ethnic Group Segregation and Civil Conflict*. Unpublished manuscript. Retrieved September 19, 2017, from https://www.cgdev.org/event/patterns-ethnic-group-segregation-and-civil-conflict

Mayoral, L. & Ray, D. (2017). *Size Matters, But Not In The Way You Think*. Unpublished manuscript. Retrieved September 19, 2017, from http://mayoral.iae-csic.org/laura_mayoral_research.htm

Michalopoulos, S. (2012). The Origins of Ethnolinguistic Diversity. *American Economic Review*, *102*(4), 1508–1539.

Michelitch, K. (2015). Does Electoral Competition Exacerbate Interethnic or Interpartisan Economic Discrimination? Evidence from a Field Experiment in Market Price Bargaining. *American Political Science Review*, *109*(1), 43–61.

Montalvo, J. G. & Reynal-Querol, M. (2005a). Ethnic Diversity and Economic Development. *Journal of Development Economics*, *76*(2), 293–323.

Montalvo, J. G. & Reynal-Querol, M. (2005b). Ethnic Polarization, Potential Conflict, and Civil Wars. *American Economic Review*, *95*(3), 796–816.

Montalvo, J. G. & Reynal-Querol, M. (2017). *Ethnic Diversity and Growth: Revisiting the Evidence* (CEPR Discussion Paper No. 12400). Centre for Economic Policy Research. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3061833

Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika*, *37*, 17–23.

Murdock, G. P. (1959). *Africa: Its Peoples and Their Culture History.* New York, NY: McGraw-Hill.

Newey, W. K. & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, *55*(3), 703–708.

Oster, E. (Forthcoming). Unobservable Selection and Coefficient Stability: Theory and Evidence. *Journal of Business & Economic Statistics*, 1–18

Pettigrew, T. F. (1998). Intergroup Contact Theory. *Annual Review of Psychology*, *49*(1), 65–85.

Raleigh, C., Linke, A., Hegre, H., & Karlsen, J. (2010). Introducing ACLED: An Armed Conflict Location and Event Dataset. *Journal of peace research*, *47*(5), 651–660.

Ramankutty, N., Foley, J. A., Norman, J., & McSweeney, K. (2002). The Global Distribution of Cultivable Lands: Current Patterns and Sensitivity to Possible Climate Change. *Global Ecology and Biogeography*, *11*(5), 377–392.

Reynal-Querol, M. (2002). Ethnicity, Political Systems, and Civil Wars. *Journal of Conflict Resolution*, *46*(1), 29–54.

Ripley, B. D. (2005). *Spatial statistics*. Hoboken, NJ: Wiley.

Rubin, D. B. (1980). Randomization Analysis of Experimental Data: The Fisher Randomization Test Comment. *Journal of the American Statistical Association*, *75*(371), 591–593.

Sundberg, R. & Melander, E. (2013). Introducing the UCDP Georeferenced Event Dataset. *Journal of Peace Research*, *50*(4), 523–532.

Theisen, O. M., Holtermann, H., & Buhaug, H. (2011). Climate Wars? Assessing the Claim That Drought Breeds Conflict. *International Security*, *36*(3), 79–106.

Vogt, M., Bormann, N.-C., Rüegger, S., Cederman, L.-E., Hunziker, P., & Girardin, L. (2015). Integrating Data on Ethnicity, Geography, and Conflict: The Ethnic Power Relations Data Set Family. *Journal of Conflict Resolution*, *59*(7), 1327–1342.

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

Appendix A Data sources

Table A.1: Data sources

Data	Source	Link	Access date
Ethnolinguistic groups	Ethnologue 17th ed., WLMS	www.worldgeodatasets.com/	2017-01-24
Conflict events	UCDP GED 5.0	ucdp.uu.se/	2016-12-20
Historical conflict	Brecke (1999), Fenske and Kala (2017)	www.jamesfenske.com/	2017-03-30
Digital elevation model	GMTED 2010 (mn30), USGS	topotools.cr.usgs.gov/	2016-05-23
Malaria Ecology Index	Kiszewski et al. (2004)	www.gordonmccord.com/	2016-12-13
Capitals	Natural Earth populated places	www.naturalearthdata.com/	2017-05-06
Country borders	Seamless Digital Chart of the World	www.worldgeodatasets.com/	2017-01-24
Agricultural land quality	Ramankutty et al. (2002)	nelson.wisc.edu/sage/	2017-04-07
Oil deposits	PETRODATA, Lujala et al. (2007)	www.paivilujala.com/	2017-02-15
Diamond deposits	DIADATA, Gilmore et al. (2005)	www.paivilujala.com/	2017-02-15
Gemstone deposits	GEMDATA, Lujala (2009)	www.paivilujala.com/	2017-02-15
Election data	Varieties of Democracy 7.1	www.v-dem.net/	2017-11-23
Population in 1990	HYDE	www.pbl.nl/hyde/	2016-03-08
Population in 2000	UNEP	na.unep.net/	2017-03-27
Population in 2000/2015	WorldPop	www.worldpop.org.uk/	2017-04-10

Notes: The listed data sources are freely accessible at the indicated URL, except for the WLMS and the Seamless Digital Chart of the World, which must be purchased.

Appendix B Local learning

B.1 Conceptual framework

In this section I analyze of local group interaction, with the intention of completing the picture of ethnic diversity in small geographical units. ELF is completely homogeneous within the unit of observation, which may conceal more subtle and complex spatial dynamics, for example local clustering. Daily interaction between groups may induce learning, leading them to behave differently towards each other than towards groups with which they have less frequent contact. Failing to properly account for this may bias the estimated coefficients in the cross-sectional test of hypothesis (1).

I adapt a measure of local interaction from Desmet et al. (2016), who study how local group interaction affects public goods provision in society at large. They motivate their paper by the contrast between contact and conflict theory. *Contact theory* (Allport, 1954) predicts that interaction between members of different groups should reduce antagonism, thereby reducing the probability of conflict. *Conflict theory* (Baker, 1934; Blumer, 1958) claims the opposite. Desmet et al. (2016) develop a model where interpersonal contact can either increase or reduce antagonism from a baseline level. Local mixing determines the frequency of interpersonal contact across ethnicities, which either reinforces or mitigates individuals' prejudice towards members of other groups. Although learning occurs locally, it has implications for antagonism against all other members of the group that an individual learns about. This means that the overall size of groups matter for the average antagonism in society. Moreover, the size of population in learning areas should matter because it determines the fraction of the total population who are learners.

Letting c denote the area of learning, local learning (LOCL) is defined, for a given unit of observation (subnational area), as:

$$\text{LOCL} = \sum_c s_c \sum_i s_{ci} \sum_j s_{cj} s_j \ , \tag{5}$$

where s_{cj}/s_{ci} is the population share of group j/i in c, s_c is the population share of area c within the unit of observation, and s_j is the population share of group j within the unit of observation. Consider the last sum. For a given member of group i, the probability of interacting with a person from group j is s_{cj}. The learning in this interaction benefits all members of group j in c, so it is weighted by s_j. Learning by group i over all groups $j \neq i$ is aggregated to c, weighted by group i's share of the population in c. Iterating this over all groups i gives the total learning that occurs in c. This learning accrues to the unit of analysis, but is weighted by s_c, because learning contributes more to the aggregate if c is relatively populous.[44]

The appropriate area within which learning should be measured is not obvious. In Desmet et al. (2016) learning occurs within 5×5 kilometer cells. The rationale is that learning requires frequent interaction, which is more likely when group members live or work close to each other. At this scale however, it becomes unclear whether we can accurately produce the population estimates necessary to calculate LOCL. Furthermore, this resolution is quite demanding on the accuracy of the data on ethnolinguistic group settlement areas. These two factors combined make it likely that LOCL will be noisily estimated. In my analysis I use areas of 0.5×0.5 degrees latitude and longitude, which is approximately 55×55 kilometers at the equator. At this scale noise is reduced, and the area reflects a (maximum) distance over which individuals can reasonably commute for work and otherwise be subjects of relatively frequent social interaction.[45]

The formula for LOCL also requires an appropriate *reference area* to determine the non-local geographical implications of local learning, captured in s_j and s_c. Here, the reference area $\equiv$ the unit of analysis, because the appropriate size of the reference area arguably depends on what is being analyzed. In Desmet et al. (2016), the unit of analysis is the country, which is reasonable given their application to public goods provision, at least if both the contribution to and provision of public goods is at the country level. That is to say, local learning affects people from the whole country because your own contribution to the public good affects people in the whole country. If however, the contribution to and provision of public goods is at the municipal level, learning about a group that is populous in another municipality is not relevant for your preference for contribution to the public good. The application to conflict is similar to the case of municipal public goods, so using the country level as the reference area is not appropriate. Learning about a group that is small in your vicinity but large somewhere else in the country is not immediately relevant for your probability to engage in conflict nearby. To see why, consider the two main direct consequences of conflict, the loss of life and the destruction of infrastructure. Both are confined to the spatial extent of fighting. You

[44] This measure is strongly related to both fractionalization and polarization. If s_j is removed from the formula, LOCL is reduced to a population-weighted average of local fractionalization. If s_j is identical to s_{cj}, so that the mixing of groups is the same at the local level (c) and in the overall society, LOCL is equivalent to a population-weighted average of polarization. Note that s_j is estimated. See section 4.2.2.

[45] This is of course sensitive to geographical variation. In parts of rural Sub-Saharan Africa, for example, 55 kilometers is way farther than the maximum commuting distance. Conditionally varying the size of learning areas is, however, not feasible.

care more about the overall loss of life if antagonism is low. The loss of infrastructure represents a negative contribution to local public goods. Hence, the spatial extent of learning should correspond to its potential to affect the probability of conflict. Since the area within which learning affects the potential for conflict is unclear, the reference area for learning varies together with the unit of analysis.

I also include an alternative "local learning" measure, which is simply fractionalization within the smallest unit of analysis (0.5 degrees), averaged within the larger units (1, 2 and 4 degrees). Note that fractionalization derived from units of different size may be highly correlated, but will likely be different in most cases. For example, overall fractionalization will be higher than local fractionalization if groups are settled in homogeneous clusters. Note that I do not propose a particular hypothesis for the direction of the correlation (for neither measure of local learning), given the contradicting predictions of conflict and contact theory.

B.2 Empirical results

In order to analyze the role of local learning, I estimate

$$\text{conflict}_{ic} = \alpha_c + \delta \text{ELF}_{ic} + \gamma \text{LOCL}_{ic} + \beta \mathbf{X}_{ic} + \varepsilon_{ic} \ , \tag{6}$$

where the only difference from equation (3) is the addition of LOCL_{ic}, defined in formula (5). As with the polarization and fractionalization measures, I take the average LOCL across all levels of the linguistic tree. To reiterate, LOCL is measured in cells of 0.5 degrees, and then aggregated up to the larger sized cells, weighted by group and cell populations. Hence, local mixing in sub-cell A with groups that are relatively populous in the larger cell B (i.e. the unit of observation), contributes to a high LOCL score if the total population share in sub-cell A within cell B is also large. LOCL is not defined for 0.5 degree cells, so I cannot estimate (6) at this level. The country level analysis is presented in Table B.3 at the end of this section.

The results from estimation of equation (6) are given in the three first columns in Table B.1. Conditional on fractionalization, local learning is negatively correlated with conflict at all grid cell resolutions, but the coefficients are not statistically significant at conventional levels. As is evident from Table B.3, there are also no significant correlations at the country level. The coefficients on ELF are comparable to those in Table 1.

In the last three columns I replace LOCL with fractionalization at 0.5 degrees, averaged within each larger cell. This constitutes an alternative measure of mixing, but without any explicit population weights. The two measures are highly correlated, with

Table B.1: Average local learning and conflict

	Fraction of years with at least one event					
	1 deg.	2 deg.	4 deg.	1 deg.	2 deg.	4 deg.
Ethnic fractionalization	0.023^{*}	0.123^{***}	0.249^{***}	0.029	0.141^{***}	0.264^{***}
	(0.013)	(0.031)	(0.066)	(0.018)	(0.037)	(0.070)
Local learning	−0.024	−0.136	−0.078			
	(0.044)	(0.096)	(0.204)			
ELF at 0.5 degrees				−0.016	-0.077^{**}	−0.086
				(0.023)	(0.038)	(0.074)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.315	0.433	0.538	0.315	0.440	0.546
N	2,148	749	304	2,304	796	314

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses with with spatial cutoff at 650 km. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

a coefficient of 0.55 at all resolutions.[46] The coefficients on ELF increase slightly, and ELF at 0.5 degrees attains a significant negative coefficient at 2 degrees.

The contact theory hypothesis presupposes that interaction translates into learning; however, it is not immediately obvious that this is a valid assumption in this context, at least not for all countries and areas. There are a number of criteria for successful contact, two of which are the ability of groups to communicate (Pettigrew, 1998) and the presence of common goals (Allport, 1954). Both of these criteria are more likely to be fulfilled if groups are linguistically and culturally close. That is to say, local exposure may not be the same as interaction. Therefore, it is reasonable to assume that contact theory is relatively more powerful than conflict theory when local learning is measured across groups defined at the lowest level of aggregation.

To investigate this possibility I classify groups at different degrees of separation, using the language tree in Ethnologue. At level 1 all languages that share the same initial ancestor are contained in one group. For example, all languages in the Niger-Congo family is now defined as one ethnolinguistic group. The most disaggregated stage is level 13, and many language groups defined at this level are sufficiently similar to be considered dialects of the same language. For ease of exposition I run present this analysis only for cells of 2 degrees, which is the unit of analysis that displayed the largest negative coefficient on local learning in Table B.1. The results are presented in Table

[46]See Figure B.1 for scatter plots.

B.2. First note that ELF is positively correlated with conflict at all levels of separation, with a slightly larger coefficient at level 9 and 13. Second, it is evident that LOCL does not appear with statistically significant coefficients at any level of separation.

Table B.2: Local learning at different levels of separation: 2 degrees

	Fraction of years with at least one event				
	Average	Level 1	Level 5	Level 9	Level 13
Ethnic fractionalization	0.123***	0.113***	0.135***	0.161***	0.164***
	(0.031)	(0.039)	(0.037)	(0.045)	(0.046)
Local learning	−0.136	0.052	−0.054	−0.093	−0.113
	(0.096)	(0.111)	(0.084)	(0.084)	(0.081)
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.433	0.434	0.420	0.424	0.430
N	749	641	680	671	672

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Geographical aggregation at 2 degrees. Conley (1999) standard errors in parentheses with with spatial cutoff at 650 km. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

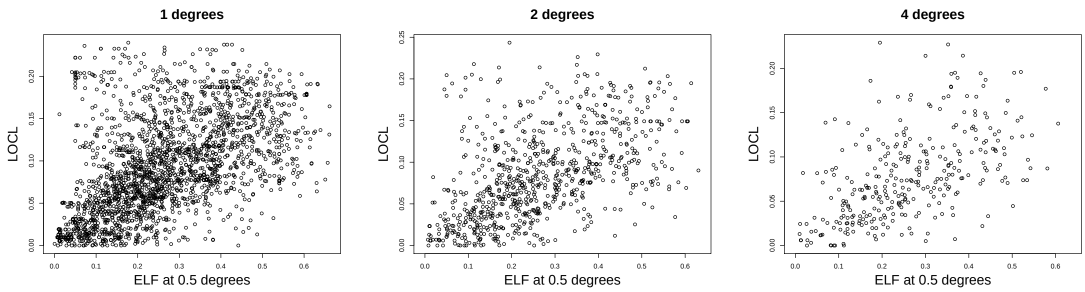


Figure B.1: ELF at 0.5 degrees and LOCL

Table B.3: Local learning at the country level

	Fraction of years with at least one event	
	(1)	(2)
Ethnic fractionalization	−0.001	0.290
	(0.275)	(0.352)
Local learning	1.955	2.151
	(1.626)	(1.668)
ELF at 0.5 degrees		−0.844
		(0.731)
Country fixed effects	No	No
Adj. R^2	0.443	0.457
N	44	44

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parentheses. Controls include the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, population in 1990 and areaAll models estimated by OLS.

Appendix C Spatial lags

The unit of observation is superimposed onto the map of ethnolinguistic groups, which means that adjacent cells are likely to contain many of the same ethnic groups, often with similar population shares. If so, neighboring observations of ELF are spatially correlated, particularly at the lowest resolutions. If diversity in neighboring cells has implications for conflict in a given unit of observation, then spatially lagged diversity is an omitted variable in (3).[47] Furthermore, conflict events in a given unit of observation are not likely to be spatially independent, and there is evidence of spatial spillovers in civil conflict (Harari & La Ferrara, 2017). If that is the case here, spatially lagged conflict is an omitted variable, and 1 will include biased estimates of the coefficient on ELF, even if spatially correlated disturbances are corrected with Conley (1999) standard errors.

In Figure C.2a I plot the average residual values in each cell against the average in their adjacent cells. The upward sloping pattern in the top plot indicates that there is substantial spatial clustering of unexplained variation in conflict at 2 degrees. As expected, spatial correlation is more pronounced at lower resolutions; the coefficient in a regression of neighbor residual on "home" cell residuals is positive and significant at 2 degrees, and close to zero and insignificant at 4 degrees. Figure C.2b reveals the same pattern for spatial correlation of ELF.[48]

The patterns in Figure C.2a are not sufficient to determine whether spatial dependence will cause the coefficients in Table 1 to be biased. If the true model contains spatial dependence only in the form of lagged error terms, OLS will be inefficient, but unbiased, and Conley (1999) standard errors will allow for correct statistical inference. If the true model includes lagged dependent or independent variables, however, coefficient estimates will be upward biased and inconsistent (Ripley, 2005).

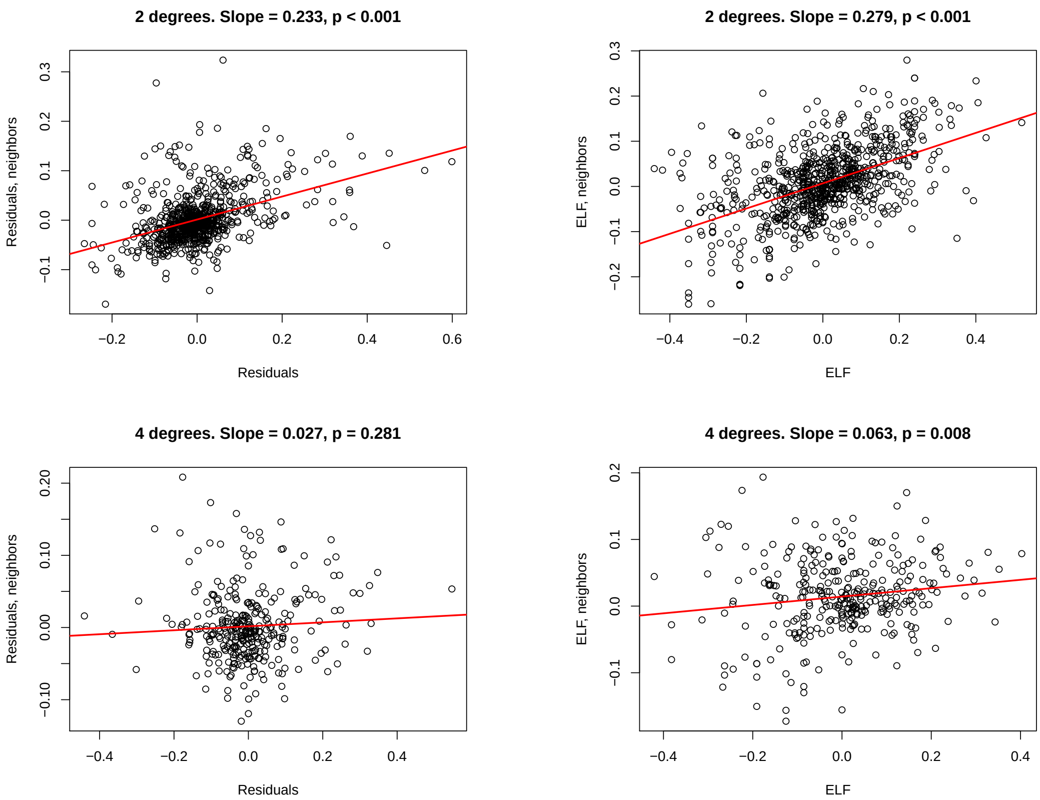
I incorporate spatially lagged dependent variables by estimating the following spatial autoregressive (SAR) model:

$$\text{conflict}_{ic} = \alpha_c + \theta \mathbf{W} \cdot \text{conflict} + \delta \text{ELF}_{ic} + \beta \mathbf{X}_{ic} + \varepsilon_{ic} \; , \tag{7}$$

where $\mathbf{W}$ is a spatial weighting matrix, conflict on the right hand side is a vector of length N, with elements containing the value of the conflict variable for each cell in the

[47] This corresponds to violation of the *stable unit treatment value assumption* first formulated by Rubin (1980).

[48] These coefficients are known as Moran's I tests in the spatial econometrics literature (Moran, 1950, 1/2).



(a) Residuals from Table 1

(b) Fractionalization

Figure C.1: Scatter plots of own-cell vs average adjacent cell values

Notes: Plots contain residuals from estimation of equation (3), with the same control variables as in Table 1. The ELF variable in the right hand side figure is deviation from country averages.

data. To account for the possibility that ethnolinguistic fractionalization affects conflict in neighboring cells, I also estimate a spatial mixed Durbin model, of the form:

$$\text{conflict}_{ic} = \alpha_c + \theta \mathbf{W} \cdot \text{conflict} + \delta \text{ELF}_{ic} + \lambda \mathbf{W} \cdot \mathbf{ELF} + \beta \mathbf{X}_{ic} + \mu \mathbf{W} \cdot \mathbf{X} + \varepsilon_{ic} \,, \qquad (8)$$

where **ELF** and **X** are the N$\times$1 vector and N$\times$K matrix for fractionalization and control variables, respectively. In the estimation of both equations, each row in **W** represents the weighting scheme for a given cell. Let Q_i be the number of "queen" neighbors for cell i, meaning surrounding cells that touch any border or corner of that cell. Each of those neighbors, at most eight, is given weight $1/Q_i$, and all other cells are given weight zero. OLS estimation of equations (7) and (8) will produce biased estimates (Anselin &

Bera, 1998), so I rely on maximum likelihood estimation.[49]

The results from estimation of equation (7) and (8) are presented in Tables C.1 and C.2 for 2 and 4 degrees, respectively.[50] I will focus the discussion on the 2 degrees table, since this cell size is more vulnerable to bias from spatial correlation. In column 1, conflict is highly correlated between neighboring cells, but the coefficient on ELF is virtually unaffected by the inclusion of a spatial autoregressive term, and stays at 0.11. In column 2, the addition of lagged independent variables decreases the coefficient on ELF, and the standard error increases, but it is still significant at 5 %.[51] The coefficient on lagged ELF is comparable in size and statistically significant at 5 %. The general lesson from Table C.1 is that both spatial autocorrelation and lagged independent variables appear to be important in themselves, but they do not affect the direct within-cell correlation between ethnolinguistic fractionalization and conflict.

Table C.1: ELF and non-state conflict: spatial lags at 2 degrees

	Fraction of years with at least one event	
	SAR model	Mixed Durbin
Ethnic fractionalization	0.110^{***}	0.082^{**}
	(0.032)	(0.038)
Conflict, spatial lag	0.461^{***}	0.479^{***}
	(0.044)	(0.046)
Ethnic fractionalization, spatial lag		0.083^{**}
		(0.041)
Country fixed effects	Yes	Yes
Log. lik.	832.997	848.573
N	796	796

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by maximum likelihood, with asymptotic standard errors.

[49] Note that the total effect of ELF_{ic} on conflict in cell i is not fully captured by δ, since it does not take into account how ELF_{ic} affects conflict in neighboring cells, and how that in turn feeds back into cell i. I disregard these indirect effects here, as explicitly modeling spatial spillovers is not within the scope of this paper.

[50] I only estimate the spatial models for 2 and 4 degrees, since these resolutions displayed positive and significant coefficients in Table 1. The spatial lag models are estimated in R, with the *lagsarlm* function of the *spdep* package (Bivand & Piras, 2015).

[51] Note that the inclusion of these spatial lags likely induces some collinearity, which will reduce precision in the estimate of the ELF coefficient.

Table C.2: ELF and non-state conflict: spatial lags at 4 degrees

	Fraction of years with at least one event	
	SAR model	Mixed Durbin
Ethnic fractionalization	0.229^{***}	0.219^{***}
	(0.052)	(0.053)
Conflict, spatial lag	0.153^{*}	-0.021
	(0.083)	(0.098)
Ethnic fractionalization, spatial lag		0.219^{***}
		(0.060)
Country fixed effects	Yes	Yes
Log. lik.	246.980	255.980
N	314	314

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by maximum likelihood, with asymptotic standard errors.

Appendix D Cross section: supplementary material

D.1 Descriptive statistics

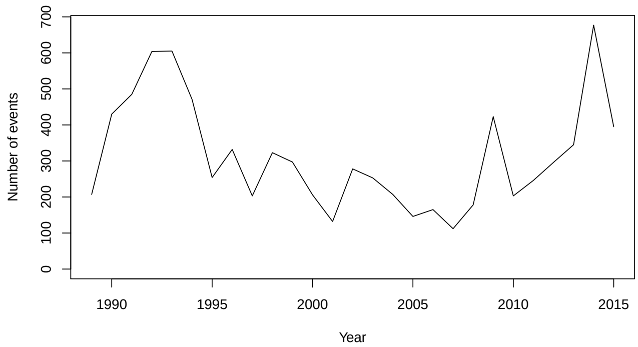


Figure D.1: Number of conflict events per year in the final sample.

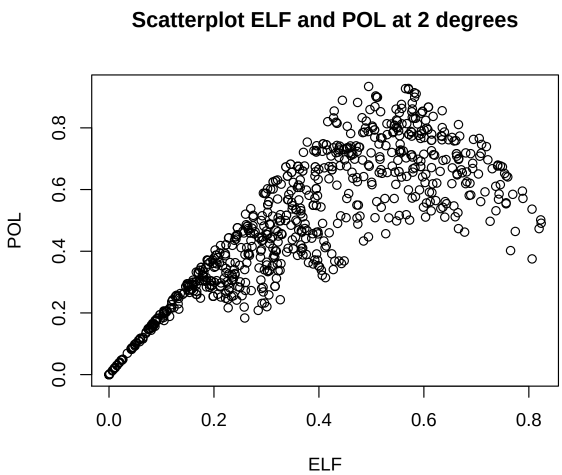


Figure D.2: Fractionalization and polarization

Notes: ELF and POL averaged over all levels of the linguistic tree.

Table D.1: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Years with > 0 conflict, fraction	7,457	0.01	0.04	0.00	0.78
Ethnic fractionalization, mean	7,457	0.25	0.19	0.00	0.80
Ethnic polarization, mean	7,457	0.36	0.26	0.00	0.97
Conflict 1400–1900, closest (km)	7,457	250.09	154.35	3.79	1,030.09
Conflict 1400–1900, count	7,457	0.04	0.42	0	13
Elevation, std.dev. (m)	7,457	83.09	98.49	0.84	1,103.32
Malaria ecology	7,457	11.45	9.68	0.00	38.08
Oil deposit	7,457	0.02	0.14	0	1
Diamond deposit	7,457	0.03	0.16	0	1
Gemstone deposit	7,457	0.03	0.17	0	1
Distance to capital (km)	7,457	589.28	399.53	0.00	1,902.25
Distance to border (km)	7,457	126.12	106.21	0.79	613.12
Population (1000 inh.)	7,457	62.43	158.47	0.02	5,244.17
Area (km^2)	7,457	2.86	0.33	0.69	3.08

Notes: Descriptive statistics at 0.5 degrees.

Table D.2: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Years with > 0 conflict, fraction	2,304	0.03	0.08	0.00	0.81
Ethnic fractionalization, mean	2,304	0.30	0.20	0.00	0.82
Ethnic polarization, mean	2,304	0.42	0.25	0.00	1.00
Conflict 1400–1900, closest (km)	2,304	253.37	158.40	0.00	1,037.12
Conflict 1400–1900, count	2,304	0.14	0.85	0	17
Soil quality, std.dev.	2,304	0.04	0.05	0.00	0.31
Elevation, std.dev. (m)	2,304	111.41	118.53	2.09	811.55
Malaria ecology	2,304	11.45	9.43	0.00	37.05
Oil deposit	2,304	0.04	0.19	0	1
Diamond deposit	2,304	0.06	0.25	0	1
Gemstone deposit	2,304	0.07	0.26	0	1
Distance to capital (km)	2,304	593.50	402.08	0.00	1,890.54
Distance to border (km)	2,304	111.69	104.96	0.96	590.36
Population (1000 inh.)	2,304	212.30	451.78	0.01	7,368.49
Area (km^2)	2,304	9.84	3.15	0.92	12.31

Notes: Descriptive statistics at 1 degree.

Table D.3: Descriptive statistics: cross-sectional data

Statistic	N	Mean	St. Dev.	Min	Max
Years with > 0 conflict, fraction	796	0.07	0.13	0.00	0.85
Ethnic fractionalization, mean	796	0.34	0.21	0.00	0.82
Ethnic polarization, mean	796	0.46	0.25	0.00	0.93
Conflict 1400–1900, closest (km)	796	256.06	161.19	6.22	1,071.55
Conflict 1400–1900, count	796	0.40	1.54	0	19
Soil quality, std.dev.	796	0.07	0.07	0.00	0.30
Elevation, std.dev. (m)	796	140.84	133.55	2.63	687.18
Malaria ecology	796	11.50	9.21	0.00	35.83
Oil deposit	796	0.06	0.24	0	1
Diamond deposit	796	0.12	0.33	0	1
Gemstone deposit	796	0.12	0.32	0	1
Distance to capital (km)	796	597.51	411.78	0.00	1,864.02
Distance to border (km)	796	98.24	97.15	3.97	573.46
Population (1000 inh.)	796	624.21	1,219.53	0.02	13,798.42
Area (km^2)	796	29.60	16.59	1.07	49.23

Notes: Descriptive statistics at 2 degrees.

Table D.4: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Years with > 0 conflict, fraction	314	0.11	0.18	0.00	0.85
Ethnic fractionalization, mean	314	0.39	0.21	0.00	0.84
Ethnic polarization, mean	314	0.48	0.22	0.00	0.90
Conflict 1400–1900, closest (km)	314	253.95	164.00	6.96	943.65
Conflict 1400–1900, count	314	1.02	2.75	0	24
Soil quality, std.dev.	314	0.09	0.08	0.00	0.32
Elevation, std.dev. (m)	314	172.74	147.86	3.59	687.27
Malaria ecology	314	11.94	8.97	0.00	34.36
Oil deposit	314	0.09	0.29	0	1
Diamond deposit	314	0.22	0.41	0	1
Gemstone deposit	314	0.18	0.38	0	1
Distance to capital (km)	314	582.07	419.52	0.00	1,816.41
Distance to border (km)	314	93.37	88.71	1.24	497.45
Population (1000 inh.)	314	1,585.95	3,067.94	0.19	32,462.28
Area (km^2)	314	76.57	62.14	1.57	196.87

Notes: Descriptive statistics at 4 degrees.

Table D.5: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Years with > 0 conflict, fraction	44	0.31	0.31	0.00	0.93
Ethnic fractionalization, mean	44	0.49	0.24	0.00	0.87
Ethnic polarization, mean	44	0.45	0.19	0.00	0.76
Conflict 1400–1900, count	44	7.09	9.24	0	44
Soil quality, std.dev.	44	0.15	0.08	0.01	0.37
Elevation, std.dev. (m)	44	265.01	163.62	15.32	711.28
Malaria ecology	44	12.54	8.10	0.00	31.36
Oil deposit	44	0.34	0.48	0	1
Diamond deposit	44	0.50	0.51	0	1
Gemstone deposit	44	0.36	0.49	0	1
Population (1000 inh.)	44	11,326.49	16,432.26	258.58	94,430.91
Area (km^2)	44	548.34	537.95	10.80	2,327.96

Notes: Descriptive statistics at the country level.

D.2 Robustness and sensitivity tests

Table D.6: ELF and non-state conflict: split by median ELF

	Fraction of years with at least one event			
	Above median ELF		Below median ELF	
	2 deg.	4 deg.	2 deg.	4 deg.
Ethnic fractionalization	0.188***	0.418***	−0.005	0.148*
	(0.062)	(0.117)	(0.049)	(0.109)
Country fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.508	0.609	0.484	0.587
N	415	164	381	150

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

Table D.7: ELF and non-state conflict: other outcomes at 2 degrees

	Non-state conflict, number of:			*State conflict, number of:*			
	deaths	events	conflicts	conflict years	deaths	events	conflicts
Ethnic frac.	0.082**	0.062**	0.121***	0.053	0.016	0.107**	0.146***
	(0.037)	(0.032)	(0.038)	(0.048)	(0.035)	(0.051)	(0.051)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.099	0.142	0.375	0.363	0.201	0.118	0.396
N	796	796	796	796	796	796	796

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses with with spatial cutoff at 650 km. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

Table D.8: ELF and non-state conflict: other outcomes at 4 degrees, with POL

	Non-state conflict, number of:			*State conflict, number of:*			
	deaths	events	conflicts	conflict years	deaths	events	conflicts
Ethnic frac.	0.353**	0.258***	0.295***	−0.256***	0.023	0.169**	0.217**
	(0.140)	(0.083)	(0.076)	(0.095)	(0.069)	(0.080)	(0.095)
Ethnic pol.	−0.264*	−0.137	−0.131	0.243***	0.035	0.041	0.043
	(0.136)	(0.083)	(0.081)	(0.085)	(0.067)	(0.091)	(0.087)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.248	0.120	0.441	0.459	0.267	0.180	0.529
N	314	314	314	314	314	314	314

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses with with spatial cutoff at 650 km. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

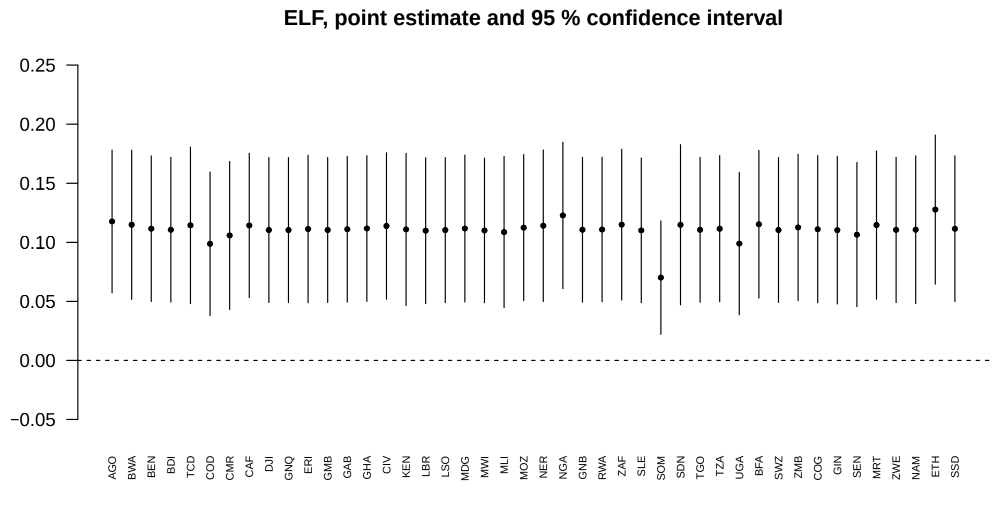


Figure D.3: Excluding countries one at a time

Table D.9: ELF and non-state conflict: exclude Somalia and Ethiopia

	Fraction of years with at least one event			
	Exclude Ethiopia		Exclude Somalia	
	2 deg.	4 deg.	2 deg.	4 deg.
Ethnic fractionalization	0.128^{***}	0.253^{***}	0.070^{***}	0.166^{***}
	(0.032)	(0.064)	(0.024)	(0.054)
Country fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.481	0.579	0.445	0.531
N	760	302	771	305

Notes: * p < 0.1; ** p < 0.05; *** p < 0.01. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

Table D.10: ELF and non-state conflict: country clustered standard errors

	Fraction of years with at least one event				
	0.5 deg.	1 deg.	2 deg.	4 deg.	Country
Ethnic fractionalization	0.004	0.020	0.110^{**}	0.240^{***}	0.203
	(0.005)	(0.016)	(0.044)	(0.080)	(0.214)
Country fixed effects	Yes	Yes	Yes	Yes	No
Adj. R^2	0.240	0.315	0.438	0.547	0.444
N	7,457	2,304	796	314	44

Notes: * p < 0.1; ** p < 0.05; *** p < 0.01. Standard errors clustered by country in all columns. All models estimated by OLS.

Table D.11: ELF and non-state conflict at 2 degrees: varying the cutoff for error correlation

	Fraction of years with at least one event					
	200 km	350 km	500 km	650 km	800 km	950 km
Ethnic fractionalization	0.110^{***}	0.110^{***}	0.110^{***}	0.110^{***}	0.110^{***}	0.110^{***}
	(0.026)	(0.028)	(0.030)	(0.031)	(0.032)	(0.034)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.438	0.438	0.438	0.438	0.438	0.438
N	796	796	796	796	796	796

Notes: * p < 0.1; ** p < 0.05; *** p < 0.01. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

Table D.12: ELF and non-state conflict at 4 degrees: varying the cutoff for error correlation

	Fraction of years with at least one event					
	200 km	350 km	500 km	650 km	800 km	950 km
Ethnic fractionalization	0.110^{***}	0.110^{***}	0.110^{***}	0.110^{***}	0.110^{***}	0.110^{***}
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.438	0.438	0.438	0.438	0.438	0.438
N	796	796	796	796	796	796

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

Table D.13: ELF and non-state conflict: allowing for cross-border correlation of errors

	Fraction of years with at least one event				
	0.5 deg.	1 deg.	2 deg.	4 deg.	Country
Ethnic fractionalization	0.004	0.020^{*}	0.110^{***}	0.240^{***}	0.203
	(0.005)	(0.012)	(0.032)	(0.061)	(0.214)
Country fixed effects	Yes	Yes	Yes	Yes	No
Adj. R^2	0.240	0.315	0.438	0.547	0.444
N	7,457	2,304	796	314	44

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

Table D.14: ELF and non-state conflict: area-weighted regression

	Fraction of years with at least one event				
	0.5 deg.	1 deg.	2 deg.	4 deg.	Country
Ethnic fractionalization	0.002	0.010	0.099***	0.217***	0.126
	(0.003)	(0.009)	(0.028)	(0.074)	(0.216)
Country fixed effects	Yes	Yes	Yes	Yes	No
Adj. R^2	0.185	0.271	0.394	0.485	0.615
N	7,457	2,304	796	314	44

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors clustered at the country level in parentheses. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

Table D.15: ELF and non-state conflict: population-weighted regression

	Fraction of years with at least one event				
	0.5 deg.	1 deg.	2 deg.	4 deg.	Country
Ethnic fractionalization	0.085***	0.068***	0.092**	0.437***	0.334
	(0.019)	(0.025)	(0.044)	(0.090)	(0.274)
Country fixed effects	Yes	Yes	Yes	Yes	No
Adj. R^2	0.364	0.499	0.670	0.749	0.643
N	7,457	2,304	796	314	44

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

Table D.16: ELF and non-state conflict: population interaction

	Fraction of years with at least one event				
	0.5 deg.	1 deg.	2 deg.	4 deg.	Country
Ethnic fractionalization	-0.007	0.009	0.125^{***}	0.195^{***}	0.313
	(0.005)	(0.013)	(0.038)	(0.068)	(0.252)
Ethnic fractionalization $\times$ population	0.166^{***}	0.047	-0.022	0.026	-0.014
	(0.058)	(0.037)	(0.032)	(0.022)	(0.023)
Country fixed effects	Yes	Yes	Yes	Yes	No
Adj. R^2	0.252	0.317	0.438	0.549	0.431
N	7,457	2,304	796	314	44

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. The population interaction has been multiplied by 1 million to improve presentation. All models estimated by OLS.

Table D.17: ELF and non-state conflict: excluded groups

	Fraction of years with at least one event				
	0.5 deg.	1 deg.	2 deg.	4 deg.	Country
Ethnic fractionalization	0.003	0.012	0.085^{***}	0.220^{***}	0.144
	(0.005)	(0.011)	(0.027)	(0.061)	(0.240)
Excluded group (≥ 1	0.001	0.005	0.003	0.037^{**}	0.236^{*}
	(0.002)	(0.005)	(0.010)	(0.022)	(0.171)
Country fixed effects	Yes	Yes	Yes	Yes	No
Adj. R^2	0.256	0.332	0.445	0.535	0.457
N	6,978	2,192	772	311	44

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

Table D.18: Cross section, average ELF

	Fraction of years with at least one conflict				
	0.5 deg.	1 deg.	2 deg.	4 deg.	Country
Ethnic fractionalization	0.004	0.020*	0.110***	0.240***	0.203
	(0.005)	(0.012)	(0.031)	(0.063)	(0.214)
Conflict 1400–1900, closest (km)	−0.010	−0.017	−0.007	0.011	
	(0.008)	(0.016)	(0.033)	(0.058)	
Conflict 1400–1900, count	−2.172	−1.710	−4.091	−4.831	−2.724
	(1.366)	(1.831)	(2.535)	(3.280)	(3.907)
Soil quality, std.dev.		0.128***	0.289***	0.347**	1.197
		(0.046)	(0.100)	(0.155)	(0.714)
Elevation, std.dev. (m)	0.033	0.046	0.037	0.045	0.167
	(0.023)	(0.044)	(0.064)	(0.120)	(0.330)
Malaria ecology	−0.063	−0.056	−0.741	−0.728	−1.825
	(0.146)	(0.337)	(0.728)	(1.538)	(8.924)
Oil deposit	11.729	20.578	28.850*	52.113**	96.862
	(7.454)	(13.175)	(16.671)	(24.845)	(129.946)
Diamond deposit	0.942	−5.509	−12.923	−26.357	−99.049
	(3.257)	(4.853)	(10.470)	(16.318)	(65.906)
Gemstone deposit	−2.141	−2.127	−3.058	−12.711	−139.477
	(3.249)	(7.529)	(14.894)	(27.225)	(106.109)
Distance to capital (km)	0.014**	0.028**	0.050**	0.080**	
	(0.006)	(0.013)	(0.022)	(0.036)	
Distance to border (km)	−0.026*	−0.041	−0.071	−0.022	
	(0.013)	(0.028)	(0.066)	(0.154)	
Population (1000 inh.)	0.067***	0.045***	0.029***	0.017***	0.007***
	(0.016)	(0.009)	(0.008)	(0.005)	(0.002)
Area (km^2)	1.536	−0.081	0.298	0.315	0.125
	(2.286)	(0.542)	(0.332)	(0.236)	(0.086)
Country fixed effects	Yes	Yes	Yes	Yes	No
Adj. R^2	0.240	0.315	0.438	0.547	0.444
N	7,457	2,304	796	314	44

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS. Coefficients on control variables except soil quality are multiplied by 1,000 in order to improve presentation. Area is in million km^2.

D.3 Tables with alternative population data

Table D.19: Cross section, average ELF: UNEP population in 2000

	Fraction of years with at least one event				
	0.5 deg.	1 deg.	2 deg.	4 deg.	Country
Ethnic fractionalization	0.009	0.028^{**}	0.100^{***}	0.219^{***}	0.202
	(0.006)	(0.013)	(0.034)	(0.063)	(0.218)
Country fixed effects	Yes	Yes	Yes	Yes	No
Adj. R^2	0.237	0.314	0.425	0.536	0.432
N	6,640	2,135	751	301	44

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

Table D.20: Cross section, average ELF: WorldPop population in 2000

	Fraction of years with at least one event				
	0.5 deg.	1 deg.	2 deg.	4 deg.	Country
Ethnic fractionalization	0.008^{**}	0.028^{**}	0.105^{***}	0.214^{***}	0.201
	(0.004)	(0.013)	(0.033)	(0.061)	(0.218)
Country fixed effects	Yes	Yes	Yes	Yes	No
Adj. R^2	0.242	0.320	0.436	0.546	0.429
N	7,851	2,366	802	314	44

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

Table D.21: Cross section, average ELF: WorldPop population in 2015

	Fraction of years with at least one event				
	0.5 deg.	1 deg.	2 deg.	4 deg.	Country
Ethnic fractionalization	0.008^{**}	0.028^{**}	0.106^{***}	0.214^{***}	0.201
	(0.004)	(0.013)	(0.034)	(0.061)	(0.217)
Country fixed effects	Yes	Yes	Yes	Yes	No
Adj. R^2	0.240	0.318	0.434	0.546	0.428
N	7,851	2,366	802	314	44

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Conley (1999) standard errors in parentheses in columns 1–4 with spatial cutoff at 650 km. Robust standard errors in column 5. Controls include the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, population in 1990 and area. All models estimated by OLS.

Appendix E Election proximity: supplementary material

E.1 Vote margins and electoral competitiveness

In Eifert et al. (2010), only the most competitive elections have a positive effect on ethnic identification, because the potential for political gain by playing the "ethnic card" depends on whether or not the electoral outcome is uncertain. If election periods are more violent because ethnic identities become more salient, we should expect competitiveness to matter also for conflict frequency. In Table E.1 I add the interaction of ELF $\times$ proximity with the difference in vote shares between the winning candidate and the runner-up in the most proximate election.[52] 244 out of 292 elections have information on vote shares, so I end up with about 15 % fewer elections to identify an effect.[53]

The triple interaction is positive at both resolutions, but imprecisely estimated at 2 degrees. The ELF $\times$ proximity coefficients are still positive, but not statistically significant. A higher margin implies lower competitiveness, so the positive interaction is at odds with the expectation that competitive elections should be more likely to experience conflict in ethnically fractionalized areas. However, the correlation is not significant at 2 degrees, so it is not a strong result. When I replace margins with the electoral competitiveness expert assessment in the interaction, there is no statistically significant coefficient, and now the ELF $\times$ proximity remains significant at 4 degrees, though with a smaller coefficient than in Table 3. I conclude that the overall results in Table E.1 do not indicate that competitive elections are particularly more prone to violence.

[52] I drop elections in which the runner-up has a higher vote share than the ultimate election winner. This can occur in cases where there is more than one round of elections, and the candidate with the highest vote share in the first round does not end up winning in the last round.

[53] 8 % of observations have these as their closest election, and are dropped as a result.

Table E.1: ELF and election proximity: electoral competitiveness

	Number of non-state conflict events			
	2 deg.	4 deg.	2 deg.	4 deg.
ELF × proximity	0.0001	0.0029	0.0005	0.0036**
	(0.0007)	(0.0025)	(0.0004)	(0.0015)
ELF × proximity × margin	0.0023	0.0087**		
	(0.0017)	(0.0040)		
ELF × proximity × competitive			0.0003	−0.0029
			(0.0017)	(0.0045)
Cell fixed effects	Yes	Yes	Yes	Yes
Country-month fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.1670	0.1608	0.1911	0.1933
N	198,956	79,343	194,314	77,866

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Spatial HAC standard errors in parentheses with spatial cutoff at 650 km and temporal cutoff at 50 months. Controls include interactions of election proximity with the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, and population in 1990. All models estimated by OLS.

E.2 Descriptive statistics

Table E.2: Descriptive statistics: monthly data

Statistic	N	Mean	St. Dev.	Min	Max
Number of conflict events	241,380	0.024	0.362	0	44
Ethnolinguistic fractionalization	241,380	0.336	0.210	0.000	0.823
Election proximity, months	241,380	−30.271	41.603	−279	0
ELF × proximity	241,380	−9.216	13.440	−135.902	0.000
Number of conflict events (demeaned)	241,380	0.000	0.322	−12.669	40.393
ELF × proximity (demeaned)	241,380	0.000	3.484	−33.768	37.839
Presidential elections since 1900	241,380	5.682	3.436	1	24
Margin, closest election	221,219	0.380	0.274	0.000	1.000
Competitiveness, closest election	217,733	0.302	0.459	0	1

Notes: Descriptive statistics at 2 degrees.

Table E.3: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Number of conflict events	93,312	0.063	0.650	0	64
Ethnolinguistic fractionalization	93,312	0.387	0.207	0.000	0.844
Election proximity, months	93,312	−29.481	40.700	−279	0
ELF × proximity	93,312	−10.590	14.734	−156.612	0.000
Number of conflict events (demeaned)	93,312	0.000	0.556	−12.672	54.941
ELF × proximity (demeaned)	93,312	0.000	3.185	−41.084	30.361
Presidential elections since 1900	93,312	5.671	3.427	1	24
Margin, closest election	85,416	0.370	0.270	0.000	1.000
Competitiveness, closest election	84,539	0.313	0.464	0	1

Notes: Descriptive statistics at 4 degrees.

E.3 Robustness and sensitivity tests

Table E.4: Election proximity without interactions

	Number of non-state conflict events	
	2 deg.	4 deg.
Election proximity	−0.0002	−0.0004
	(0.0003)	(0.0009)
Cell fixed effects	Yes	Yes
Country-month fixed effects	No	No
Country-year fixed effects	Yes	Yes
Adj. R^2	0.1275	0.1595
N	249,156	94,608

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Spatial HAC standard errors in parentheses with spatial cutoff at 650 km and temporal cutoff at 50 months. All models estimated by OLS.

Table E.5: ELF and election proximity: parliamentary elections

	Number of non-state conflict events			
	2 deg.	4 deg.	2 deg.	4 deg.
ELF × parliamentary election proximity	0.0006	0.0049^{**}	0.0001	−0.0003
	(0.0006)	(0.0021)	(0.0006)	(0.0022)
ELF × presidential election proximity			0.0007^{*}	0.0058^{***}
			(0.0004)	(0.0016)
Cell fixed effects	Yes	Yes	Yes	Yes
Country-month fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.1596	0.1409	0.1661	0.1598
N	248,832	98,172	215,784	86,184

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Spatial HAC standard errors in parentheses with spatial cutoff at 650 km and temporal cutoff at 50 months. Controls include interactions of election proximity with the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, and population in 1990. All models estimated by OLS.

Table E.6: ELF and election proximity: country clustered standard errors

	Number of non-state conflict events	
	2 deg.	4 deg.
ELF × proximity	0.0007	0.0054^{***}
	(0.0005)	(0.0019)
Cell fixed effects	Yes	Yes
Country-month fixed effects	Yes	Yes
Adj. R^2	0.1654	0.1581
N	215,784	86,184

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors clustered at the country level in parentheses. Controls include interactions of election proximity with the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, and population in 1990. All models estimated by OLS.

Table E.7: ELF and election proximity: bandwidths around election month

	Number of non-state conflict events					
	2 deg.	4 deg.	2 deg.	4 deg.	2 deg.	4 deg.
ELF × proximity	0.0009^{**}	0.0060^{***}	0.0008^{**}	0.0059^{***}	0.0008^{**}	0.0059^{***}
	(0.0004)	(0.0016)	(0.0004)	(0.0016)	(0.0004)	(0.0016)
ELF × proximity × 18 mos.	0.0030^{***}	0.0095^{***}	0.0034^{***}	0.0098^{***}	0.0032^{***}	0.0097^{***}
	(0.0011)	(0.0037)	(0.0011)	(0.0033)	(0.0011)	(0.0035)
ELF × proximity × 12 mos.			−0.0019	−0.0018	−0.0016	−0.0017
			(0.0023)	(0.0068)	(0.0020)	(0.0059)
ELF × proximity × 6 mos.					−0.0031	−0.0017
					(0.0060)	(0.0175)
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.1654	0.1582	0.1654	0.1582	0.1654	0.1582
N	215,784	86,184	215,784	86,184	215,784	86,184

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Spatial HAC standard errors in parentheses with spatial cutoff at 650 km and temporal cutoff at 50 months. Controls include interactions of election proximity with the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, and population in 1990. All models estimated by OLS.

Table E.8: ELF and election proximity: alternative outcomes at 2 degrees

	Non-state conflict:			*State conflict*			
	dummy	deaths	conflicts	events	dummy	deaths	conflicts
ELF × proximity	0.0003***	0.0025**	0.0004***	0.0023***	0.0003***	−0.0023	0.0004***
	(0.0001)	(0.0012)	(0.0001)	(0.0004)	(0.0001)	(0.0056)	(0.0001)
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.1741	0.0003	0.1765	0.2573	0.1944	0.0268	0.2132
N	215,784	215,784	215,784	215,784	215,784	215,784	215,784

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Spatial HAC standard errors in parentheses with spatial cutoff at 650 km and temporal cutoff at 50 months. Controls include interactions of election proximity with the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, and population in 1990. All models estimated by OLS.

Table E.9: ELF and election proximity: all control variables

	Number of non-state conflict events	
	2 deg.	4 deg.
Proximity interacted with:		
Ethnic fractionalization	0.0007*	0.0054***
	(0.0004)	(0.0015)
Conflict 1400–1900, closest (km)	−0.0002	0.0016
	(0.0006)	(0.0019)
Conflict 1400–1900, count	−0.0342	−0.1427
	(0.0748)	(0.1301)
Soil quality, std.dev.	0.0013	0.0006
	(0.0013)	(0.0023)
Elevation, std.dev. (m)	0.0008	0.0043*
	(0.0006)	(0.0022)
Malaria ecology	−0.0074	−0.0252
	(0.0086)	(0.0331)
Oil deposit	0.0901	−0.3700
	(0.1324)	(0.4913)
Diamond deposit	−0.2025**	−0.3312
	(0.0788)	(0.2485)
Gemstone deposit	−0.4339	−0.8412
	(0.3689)	(0.6575)
Distance to capital (km)	0.5252***	1.6259***
	(0.1654)	(0.5136)
Distance to border (km)	−0.0001	−0.0017
	(0.0004)	(0.0023)
Population (1000 inh.)	0.2771	0.4355*
	(0.2094)	(0.2402)
Cell fixed effects	Yes	Yes
Country-month fixed effects	Yes	Yes
Adj. R^2	0.1654	0.1581
N	215,784	86,184

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Spatial HAC standard errors in parentheses with spatial cutoff at 650 km and temporal cutoff at 50 months. All models estimated by OLS. Coefficients on control variables except soil quality are multiplied by 1,000 in order to improve presentation.

E.4 Tables with alternative population data

Table E.10: ELF and election proximity: UNEP population in 2000

	Number of non-state conflict events	
	2 deg.	4 deg.
ELF × proximity	0.0007*	0.0050***
	(0.0004)	(0.0015)
Cell fixed effects	Yes	Yes
Country-month fixed effects	Yes	Yes
Adj. R^2	0.1634	0.1559
N	201,204	81,972

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Spatial HAC standard errors in parentheses with spatial cutoff at 650 km and temporal cutoff at 50 months. Controls include interactions of election proximity with the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, and population in 1990. All models estimated by OLS.

Table E.11: ELF and election proximity: WorldPop population in 2000

	Number of non-state conflict events	
	2 deg.	4 deg.
ELF × proximity	0.0011**	0.0051***
	(0.0004)	(0.0015)
Cell fixed effects	Yes	Yes
Country-month fixed effects	Yes	Yes
Adj. R^2	0.1659	0.1581
N	217,728	86,184

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Spatial HAC standard errors in parentheses with spatial cutoff at 650 km and temporal cutoff at 50 months. Controls include interactions of election proximity with the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, and population in 1990. All models estimated by OLS.

Table E.12: ELF and election proximity: WorldPop population in 2015

	Number of non-state conflict events	
	2 deg.	4 deg.
ELF × proximity	0.0011**	0.0051***
	(0.0004)	(0.0015)
Cell fixed effects	Yes	Yes
Country-month fixed effects	Yes	Yes
Adj. R^2	0.1659	0.1580
N	217,728	86,184

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Spatial HAC standard errors in parentheses with spatial cutoff at 650 km and temporal cutoff at 50 months. Controls include interactions of election proximity with the distance to closest historical conflict, the number of historical conflicts, standard deviation of soil quality, standard deviation of elevation, the malaria ecology index, dummies for oil, secondary diamond and gemstone deposits, distance to capital, distance to border, and population in 1990. All models estimated by OLS.