Local Ethno-Political Polarization and Election Violence in Majoritarian vs. Proportional Systems

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Abstract

How does local ethnic demography affect the conduct of majoritarian elections? Because legislative elections in majoritarian systems are contested locally, local ethno-political polarization increases the risk of pre-election violence. In districts that are polarized between politically competing ethnic groups, violence can be targeted with comparative ease at opposing voters, and can, if perpetrated collectively, mobilize the perpetrators' co-ethnics. I expect no such dynamics in PR systems where political competition plays out at higher geographical levels. To test this argument, I combine new data on the ethnic composition of local populations in 22 African countries with monthly data on riots and survey data on campaign violence. Ethno-politically polarized districts in majoritarian and mixed electoral systems see substantively larger increases in the number of riots prior to legislative elections and more fear of pre-election violence among citizens than non-polarized districts in the same country and at the same time. I do not find these patterns in PR systems. The results enhance our understanding of how electoral systems interact with local ethnic demography in shaping pre-election violence.

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Introduction

Choices over the design of electoral systems in ethnically divided societies are most influential in determining the fate of democracy and peace in a polity. Addressing electoral violence as a vital threat to democracies around the globe, this article analyzes the impact of local ethnic demography on violence preceding legislative elections in Africa. In particular, I argue that local competition between politically mobilized ethnic groups increases the risk of violence before majoritarian but not proportional legislative elections.

The literature on the vices and virtues of majoritarian and PR systems in ethnically divided societies is, beginning with the seminal contributions of Horowitz (1990, 1991, 1994) and Lijphart (1985) and Lijphart and Aitkin (1994), extensive. It mostly focuses on the effects of electoral systems on political parties, post-conflict stability, and the risk of civil war in general.[1] Studying the effects of electoral systems on electoral violence, Birch (2007) and Fjelde and Höglund (2016) present country-level evidence that majoritarian elections come with more misconduct and campaign violence than PR systems, in particular where ethnic groups are excluded from political power. However and despite Birch's (2007) theoretical insight that election violence in majoritarian systems is caused by local competition, prevailing country-level research does not shed empirical light on why campaigns turn violent in some constituencies but not in others (Birch et al., 2020). Furthermore, not all types of electoral competition may lead to equal levels of violence. Focusing on competition along ethnic cleavages, this study addresses these issues with high-resolution spatio-temporal data that evidence the violent consequences of local competition between politically mobilized ethnic groups in majoritarian elections.

Drawing on the incentives set by the structure and geographic locus of competition in majoritarian legislative elections, I argue that local political competition between ethnic groups incentivizes violent campaigning in majoritarian systems. In ethno-politically polarized constituencies, violence can be effectively targeted and, especially when it comes in the form of a riot, serves the purpose of polarizing the electorate. In contrast, local ethno-political competition does not increase the risk of violence before PR elections, where legislative elections are contested at the regional or national level making local ethnic polarization inconsequential for campaign strategies.

With this focus on local ethno-political competition, the argument builds on

[1] On electoral systems and voting in ethnically diverse polities see, e.g., Neto and Cox (1997), Ordeshook and Shvetsova (1994), and Mozaffar et al. (2003); on post-conflict stability Bogaards (2013), and on civil wars Schneider and Wiesehomeier (2008).

and extends previous research that understands pre-election violence as intending to "influence the electoral process and in extension its outcome" (Höglund, 2009, 417; Birch et al., 2020). Pre-election violence can increase the odds of victory of its instigator through the polarization of the electorate (Dercon and Gutiérrez-Romero, 2012; Horowitz, 2001; Wilkinson, 2004) and the demobilization of his opponent's voters by means of intimidation, displacement, and death (Bratton, 2008; Collier and Vicente, 2014; Klopp, 2001; Steele, 2011).[2] It not only affects nation-wide official elections, but also intra-party contests (Goldring and Wahman, 2018; Bech Seeberg et al., 2018; Reeder and Seeberg, 2018). In parallel to incentives to campaign peacefully, violence is most likely to accompany contested campaigns (Hafner-Burton et al., 2013; Salehyan and Linebarger, 2015; Wilkinson, 2004), in particular those led by incumbents (Taylor et al., 2017; Rauschenbach and Paula, 2019).

I test the argument that local ethno-political competition increases the risk of violence before majoritarian but not PR elections with new spatial data on the ethnic composition of local populations in 22 African countries between 1990 and 2013, mostly countries with unconsolidated democratic institutions and recurring electoral violence (Goldsmith, 2015). The main analysis studies the effect of local ethno-political competition on local pre-election increases in rioting. Districts that are polarized between politically mobilized ethnic groups experience steeper increases in rioting prior to majoritarian elections than non-polarized districts. Consistent with the argument, this effect is absent in PR systems.

Rigid two-way fixed effects and controls for spatio-temporal autocorrelation restrict the potential of spurious results. The findings are robust to using different data on rioting and pre-election violence, and are not due to reverse causality in the timing of elections and local ethnic demography, or endogenous district boundaries. In addition, I find that survey respondents' fear and experience of pre-election violence increases with the level of local ethno-political polarization in majoritarian but not proportional electoral systems.

The consistent empirical evidence supports the theoretical argument and contributes to our understanding of the effects of ethnic geographies on the conduct of majoritarian elections in Africa. They also supply evidence on the local drivers of electoral violence to those who try to prevent it. Further discussed in the conclusion, the results provides additional detail to the existing literature on drawbacks of majoritarian electoral systems in multi-ethnic and unconsolidated democracies. The findings also highlight the effect of the spatial design of electoral districts on the (violent) conduit of elections.

[2] Electoral violence leads to mixed effects on turnout (Bekoe and Burchard, 2017).

The geography of ethno-political competition and violence before legislative elections

Campaign violence is often argued to be "produced" (Brass, 2011) by political elites and their henchmen trying to increase their chances at the ballot box (Collier and Vicente, 2014, 2011; Horowitz, 2001; Wilkinson, 2004). Particularly in ethnically divided constituencies, candidates might choose to deliberately incite ethno-nationalist discourses and plan inter-ethnic violence. Such patterns have affected, for example, elections in India (Brass, 2011; Wilkinson, 2004) and the 1992 Kenyan legislative election (Throup and Hornsby, 1998). Here, incumbent MPs of the *Kenya African National Union* (KANU), traditionally associated with the Kalenjin, were involved in inciting riots against ethnic Kikuyu, Kisii, Luo, and Luhya, leading to the displacement of 300,000 and the death of 1,500 (Africa Watch, 1993; Klopp, 2001). However, violence did not break out everywhere in the country. Instead, closely contested precincts with non-Kalenjin swing-voters saw most rioting, which may have actually harmed the prospects of KANU candidates elsewhere (Klopp and Zuern, 2007; Throup and Hornsby, 1998).

In (cynical) parallel to monetary expenditures (Cox and Munger, 1989; Erikson and Palfrey, 2000; Pattie et al., 1995), the likelihood of instrumental campaign violence increases with the probability that it turns an election to the benefit of its instigator. As the Kenyan experience illustrates, campaigns are therefore most likely to come with substantial bloodshed where races are expected to be close (Hafner-Burton et al., 2013; Klopp and Zuern, 2007; Salehyan and Linebarger, 2015; Wilkinson, 2004). Only then do the expected benefits of violence outweigh its costs, which consists in material payments for those who perpetrate the violence, the risks of alienating voters (e.g. Gutiérrez-Romero and LeBas, 2020), and potential judicial persecution.

In addition to influencing pivotal voters' turnout and choice, electoral violence can also aim at affecting election timing, either preventing a poll from happening or forcing one to be held. While this is an important dynamic, electoral violence of this type will be conducted differently, not targeting pivotal voters but aiming to pressure the executive, legislator, and/or electoral commission into changing the electoral timetable. Because of this difference in strategic goals, the theoretical argument concerns violence as a strategy used to maximize perpetrators' chances of winning scheduled and undelayed elections. I will, however, return to the effect of violence on the timing of elections as an empirical challenge.

For pre-election violence to be effective in maximizing instigators' chance of victory, it must be targeted at the voters of the perpetrator's opponent(s). In contrast to ideologically motivated electoral preferences, perpetrators of campaign violence can discern prospective vote choices that follow ethnic identities (Horowitz, 2001). Since many voters in multi-ethnic societies base their vote to a significant – but not exclusive[3] – degree on ethnic attributes of candidates such as language, religion, or name (Adida, 2012; Basedau et al., 2011; Bratton et al., 2012; Bratton and Kimenyi, 2008; Chandra, 2004), perpetrators can use the same characteristics to target their violence.[4] But the politicization of ethnicity does not only facilitate the violent demobilization of electoral opponents. It also increases the mobilizing effect of violence has on perpetrator's supporters, since it highlights ethnic differences and incites ethno-nationalist sentiments (Dercon and Gutiérrez-Romero, 2012; Horowitz, 2001; Wilkinson, 2004). The resulting ideological polarization of the electorate coincides with the increase in the salience of ethnic identities brought about by contested electoral campaigns (Eifert et al., 2010).

However, not all forms of violence suit the goals of the perpetrators of electoral violence in ethnicized polities. To achieve the first aim of demobilizing opposing voters, violence has to be ethnically targeted to such an extent as to induce sufficient fear among them and their co-ethnics. As to pursue the second goal, raising the salience of ethnic identities among the voters of the violence-inducing candidate himself, the demographic basis of those who perpetrate the violence has to be equally broad. Only if a sufficient number of people participate in the violence can a public arousal of sentiment be achieved (Brass, 2011). With these two goals of pre-election violence in ethnicized polities in mind, the ethnic riot fits the incentives of the instigators of pre-election violence better than other forms of collective violence. This is because an ethnic riot, defined here as "intense, sudden, though not necessarily wholly unplanned, lethal attack by civilian members of one ethnic group on civilian members of another ethnic group" (Horowitz, 2001, 1), combines popular mobilization with selective targeting of ordinary members of the ethnic 'other' (Wilkinson, 2004). Violence perpetrated by state or non-state organizations typically lack the widespread mobilization of ethnic groups against each other.

In addition, rioting is a form of medium-scale violence with a relatively low risk of punishment. Given its broad demographic basis, even independent prosecutors may find it difficult to expose the planners behind riotous masses after the fact. In contrast, violence executed by organized structures such as the police, political parties, and militias leaves more traces for prosecution and punishment. The argument

[3] See, e.g. Ichino and Nathan (2013).

[4] See Fearon (1999) on politicians' strategy to use the same markers to deliver 'pork' to their co-ethnics.

that riots are particularly "effective" instruments of ethnic campaign violence does however not entail that electoral violence takes no other form.

The previous reasoning motivates the claim that political competition between ethnic groups increases the risk of pre-election violence, in particular of riots. Since the degree to which the competition for political power is ethnicized is strongly related to the electoral design of a multi-ethnic society,[5] the electoral system likely also affects the extent to which one should expect violent legislative campaigns. The literature on electoral systems consists roughly of two camps. The first holds that PR leads to equal representation of all ethnic groups, facilitating power-sharing, preventing the political domination of single groups, and thus fostering peace (Lijphart and Aitkin, 1994; Schneider and Wiesehomeier, 2008).Critics of this view hold that PR encourages ethnic mobilization and perpetuates divisions along main cleavages (Horowitz, 1991, 167-172). Instead, they argue that ethnically divided societies should conduct elections following plurality rules, in particular using the 'single transferable' or 'alternative' vote that encourage cross-ethnic alliances and intra-ethnic divisions (Horowitz, 1991, 1985). Empirically however, PR systems exhibit lower degrees of ethnicization of political preferences than majoritarian systems (Huber, 2012). This coincides and Fjelde and Höglund's (2016) finding that majoritarian countries in Africa exhibit more electoral violence than proportional ones,[6] especially where large ethnic groups are excluded from political power.

Notwithstanding its merits, many proponents of proportional vs. majoritarian voting do not sufficiently consider the importance of the geography of ethnic cleavages when assessing the (violent) consequences of both (cf. Barkan et al., 2006; Wagner and Dreef, 2013).[7] Because majoritarian elections are contested locally, the geography of political preferences is a key determinant of the degree of competition in a country's electoral districts (Sartori, 1997).[8] Consequently, the risk of pre-election riots under ethnicized voting in a majoritarian system is co-determined by the extent to which local constituencies are divided between ethnic groups. The risk of pre-election riots will be highest in an ethno-politically polarized constituency with two politically mobilized ethnic groups of equal size. The risk of campaign riots decreases as the number of groups in a constituency and/or their heterogeneity in size increases. Both factors decreases competition between them.

[5]See Bogaards (2013) for a review.

[6]For evidence from post-communist countries, see Birch (2007).

[7]A similar disregard affects studies of the impact of ethnic heterogeneity on electoral parties (Neto and Cox, 1997; Ordeshook and Shvetsova, 1994). But see Mozaffar et al. (2003).

[8]In extension, the geographic distribution of partisan preferences influences the complex translation of votes to assembly seats in majoritarian polities (Barkan et al., 2006; Calvo and Rodden, 2015; Gudgin and Taylor, 2012; Rodden, 2010).

Hypothesis 1: *Local polarization between politically mobilized ethnic groups increases pre-election rioting in majoritarian electoral systems.*

The link between local political competition among ethnic groups and campaign riots is thus contingent on the nature of majoritarian systems and the locus of their electoral contests. Fundamentally different geographical patterns of pre-election violence should therefore be observed in pure PR systems, which I analyze as a control group only. Under PR voting, competition takes place at supra-local level, mostly at the region- or country-level. Thus, regional or national characteristics will shape incentives for violent campaigning before elections. In contrast, the degree of *local* ethno-political polarization will not influence considerations about where to best incite riots before an election since it does not strongly determine the share of votes won by parties. In a proportional contest, it is less 'effective' to target ethnically mixed areas than those homogenously inhabited by one's opponents – a strategy that South Africa's ANC pursued in the first post-apartheid election in 1994 (Klopp and Zuern, 2007). In addition and as Birch (2007) points out, parties in PR systems pool the risks and benefits of electoral campaigning. They are thus less vulnerable to the collective action problems faced in majoritarian systems (Carey and Shugart, 1995) and have greater powers to maintain their credibility and avoid violence during electoral campaigns altogether. I thus expect the following contrast between violence before majoritarian and PR elections:

Hypothesis 2: *Local polarization between politically mobilized ethnic groups increases pre-election rioting more in majoritarian than in proportional electoral systems.*

Local ethno-political competition and pre-election riots

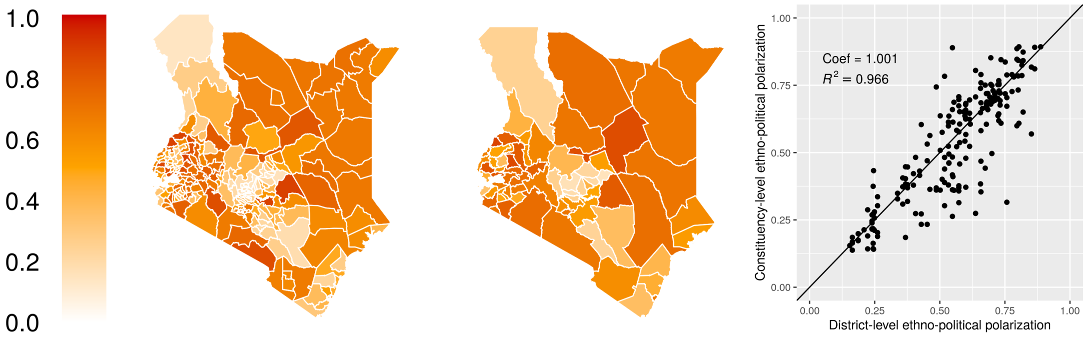
To test the arguments' two main hypotheses, I combine data on the ethnic composition of African districts with monthly riot data to model local increases of the number of riots prior to legislative elections. The main empirical strategy models differences in the pre-election increase of the monthly number of riots as legislative elections approach in ethno-politically polarized and non-polarized districts (see also Harish and Little, 2017; Goldsmith, 2015). The focus on the pre-election *increase* in violence comes closer to the hypothesized causal mechanism than other models on the link between electoral competition and local-level violence. These either compare average levels of violence across units of analysis[9] or restrict the sample to election periods only (e.g. Hafner-Burton et al., 2013; Daxecker et al., 2019). While the former strategy does not yield evidence on the *electoral* character of violence, the latter strategy lacks the crucial comparison of violence during months directly before an election with violence occurring at other points in time. It therefore risks confounding units that *always* experience violence in a manner unrelated to elections with those that are affected by violence only around elections.

The empirical analysis finds that ethno-politically polarized districts see an escalation of rioting before majoritarian legislative elections that is much more severe than the escalation observed in non-polarized districts or before legislative elections under proportional voting. This result is robust to various permutations of the baseline model. In addition, similar effects of local ethno-political polarization affect citizens' surveyed fear of pre-election violence in majoritarian systems. I do not extend the analysis to cover post-election violence, which does not have a direct effect on the outcome of the election itself and is therefore presumably motivated by a different logic than outlined above.

Data

The district-month in 22 African countries between 1990 and 2013 constitutes the fundamental unit of analysis. Yearly varying data on the spatial extent of districts, defined as the second administrative level in states, comes from FAO's (2014) GAUL database. Administrative units as units of analysis might seem inferior to using electoral districts where electoral competition takes place. However, there is no comprehensive cross-national data on electoral districts available to date. More importantly, taking electoral districts as units of analysis would make a comparison between majoritarian and PR systems all but impossible, because electoral districts created for majoritarian elections do not exist in PR systems. Because electoral districts in majoritarian systems are typically nested within administrative units, measures for administrative districts are expected to be a reliable proxy for those on the level of majoritarian constituencies – real ones in majoritarian systems and 'counterfactual' constituencies in PR systems. Figure 1 illustrates this notion for Kenya in 2007. District-level ethno-political polarization explains 97% of the varia-

[9] Most prominently, Wilkinson (2004) argues that party-competition in Indian states increases the odds of Hindu-Muslim riots. He then models riots as a function of the additive effects of electoral proximity and party-competition. This leaves the interaction of the two variables, the center of the theoretical argument, unexplored.



(a) Constituency-level (b) District-level (c) Comparison

Figure 1: Ethno-political polarization in Kenya

tion found at the constituency-level.[10]

The main dependent variable is the monthly count of riots. This data comes from the geocoded Social Conflict in Africa Data (SCAD 1990-2013; Salehyan et al., 2012), where riots are defined as "[d]istinct, continuous and violent action directed toward members of a distinct 'other' group or government authorities" (Salehyan and Hendrix, 2017, 4). This definition roughly coincides, except for the ethnic modifier, with the definition of the 'ethnic riot' given above. Because of the difficulty to distinguish without much bias ethnic from non-ethnic riots in newspaper sources, I take the raw riot count as the best fitting measure of rioting. I furthermore discuss analyses of the subsets of spontaneous, ethnic, and election-related rioting.[11]

Riot-events are spatio-temporally matched to district-polygons and aggregated to the monthly level.[12] To compare the robustness of the results with different conflict data (Hegre and Sambanis, 2006), I complement the analysis with counts of riots and riot-fatalities from the ACLED data (Raleigh et al., 2010) and the geocoded ECAV data on electoral violence (Daxecker et al., 2019).[13] Throughout, I take the natural logarithm of the count of riots and riot fatalities +1 as the dependent variable to alleviate the variables right-skew and to follow the intuition that the increase from 0 to 1 riot is larger than moving from 3 to 4 riots.

To model the increase of rioting prior to legislative elections, each district-month is associated with its temporal distance to the next legislative election. Data on the date of elections comes from the National Elections across Democracies and

[10] Appendix A2.6 compares district- with constituency-level results on pre-election rioting in Kenya.

[11] Note that the identification of these subsets of riots requires more information coded from news reports which may exacerbate reporting bias.

[12] I drop events without coordinates and attribute the few multi-month riots to their first month.

[13] As highlighted above, this data does not allow for observing *increases* in violence as elections approach as it lacks data on violence in non-campaign periods.

Autocracies data (NELDA v4; 1989-2012; Hyde and Marinov, 2011).[14] Because the 'effectiveness' of violence likely increases exponentially as elections come closer (Harish and Little, 2017), the variable `time to election` is calculated as the inverse of the distance to the next legislative election (after adding 1 to divide by 0 in election months). The variable thus increases exponentially as an election comes closer. This is more realistic, more flexible, and does fit the data better than a simpler pre-election dummy (see Figure 3). A robustness check drops all elections that have not been held at their scheduled data, showing that the results are not driven by endogenous election timing.

To differentiate majoritarian elections from proportional voting, I rely on the World Bank Data on Political Institutions (Beck et al., 2001). The data encode whether legislators are elected using a first-past-the-post or winner-takes-all rule. This coding includes 5 mixed majoritarian and PR systems[15] for which, according to the argument presented above, incentives for pre-election violence should be higher in ethno-politically polarized single-member-districts as well.[16]

I measure the degree of local ethno-political polarization by computing a polarization index with data on local ethnic demographics and the political relevance of ethnic groups. The first input consists in maps of the ethnic composition of local populations in Africa (Spatially Imputed Data on Ethnicity SIDE; Müller-Crepon and Hunziker, 2018).[17] The data are constructed by spatially imputing the ethnic composition of geocoded survey-clusters enumerated in USAID's Demographic and Health Surveys (DHS, 2018). Using non-parametric modeling techniques, Müller-Crepon and Hunziker (2018) impute the survey data over a grid with a resolution of 8.3×10^{-3} degrees ($\sim$1km). As an indication of its reliability, the SIDE data exhibits substantial overlap with local level census data from Uganda and Senegal. Since the SIDE maps are available for different years, I take the most recent map available for every district-month. Where no past maps are available, the most proximate map from the following years is used (Figure A1 in the Appendix).

Based on the SIDE data, I construct the measure for local ethno-political polarization in four steps visualized in Figure 2. To move from ethnic compositions of local populations to their composition in terms of politically mobilized ethnic

[14] I extend the data to December 2014 to make use of the full set of SCAD events. I drop all months further away from the next election than 5 years.

[15] Cameroon, DRC Congo, Guinea, Niger, and Senegal; cf. Figure A1.

[16] The data cover all years up to 2012 and has been extended to 2013. I ensure that codings for elections that follow changes of electoral rules (e.g. Togo 2007) reflect the systemic incentives for electoral violence.

[17] SIDE provides compositional, cross-national data on ethnic geographies, overcoming a lack of micro-level census data in many developing countries and the inadequacy of polygon-based data (such as GeoEPR; Wucherpfennig et al., 2011) on the matter.

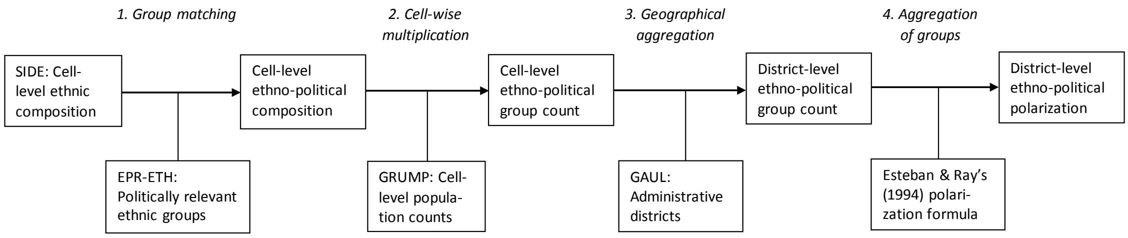


Figure 2: Flowchart of the construction of the measure of district-level ethno-political polarization.

groups, I first match the SIDE data with the Ethnic Power Relations dataset (EPR; Cederman et al., 2010; Vogt et al., 2015). This dataset provides a time-varying list of ethnic groups that are politically mobilized by at least one actor at the national level or that are politically discriminated against by the state. The coding of political mobilization is most often based on the existence of ethnically mobilizing parties or politicians. Because MPs are often part of larger ethnic coalitions,[18] the data fits the proposed theoretical argument well. I match ethnic groups in SIDE with their EPR counterparts for every year between 1990 and 2013.[19] Groups in SIDE without an equivalent in EPR are coded as being politically irrelevant.

In a second step, I weigh each grid-cell with its population in a given year.[20] I then aggregate the resulting grid of head-counts of politically relevant ethnic groups to the district-year polygons introduced above (step 3). In the fourth step, I use the yearly ethno-political composition of districts to derive the measure for local ethno-political polarization (see Figure 1), applying the standard formula for polarization introduced by Esteban and Ray (1994).[21]

[18] For the case of Kenya, see e.g. Throup and Hornsby (1998).

[19] The matching procedure is base on either (1) string matching, (2) a search on the Joshua Project's and Ethnologue's websites, (3) or, lastly, a Wikipedia search. I drop SIDE maps in which groups correspond to multiple EPR groups since they would mismeasure ethno-political polarization. This affects maps from Ghana after 2002, Cameroon after 2010 and the Côte d'Ivoire after 1993.

[20] Population data for the years 1990, 1995, and 2000 comes from CIESIN et al. (2011).

[21] Ethno-political polarization$_{dy} = 4 * \sum_{i \in I_{dy}} (size_i^2 * (1 - size_i))$, with $size_i$ being the size of ethnic group i relative to all politically relevant groups I populating a district d in a particular year y.

Empirical strategy

Using the resulting dataset, I model the effect of ethno-political polarization on the increase in rioting prior to elections as a linear count model:

$$\begin{aligned}\mathsf{riot}_{dcym} = \boldsymbol{E}_{dcym} + \beta_1 \mathsf{time\ to\ election}_{mc} + \beta_2 \mathsf{ethno\text{-}political\ polarization}_{dy} + \\ \beta_3 \mathsf{time\ to\ election}_{mc} \times \mathsf{ethno\text{-}political\ polarization}_{dy} + \delta \boldsymbol{X}_{dm} + \epsilon_d,\end{aligned}$$

where $riot_{dcym}$ is the logged count of riots in district d and month m of year y which is associated with a time to the next election in its country c, with the level of ethno-political polarization, and, crucially, the interaction between the two. The coefficient of the interaction term tests Hypothesis 1, whether ethno-political polarization increases the pre-election rise in rioting. Since ethnic heterogeneity and polarization is expected to be higher in populated districts, which also experience more riots, districts' logged population and its interaction with time to election are controlled for ($\boldsymbol{X}_{dm}$). To test Hypothesis 2, I interact these right-hand terms with the dummy for proportional systems. The coefficient of $\mathsf{time\ to\ election}_{mc} \times \mathsf{ethno\text{-}political\ polarization}_{dy} \times \mathsf{PR}_{cy}$ captures the difference of the effect of polarization on the pre-election rise in riots between majoritarian and PR elections.

In comparison to count models such as the negative binomial model, the linear model allows for adding a flexible set of spatio-temporally defined fixed effects $\boldsymbol{E}_{dcym}$. Narrowing the scope of these fixed effects, the fully specified model includes fixed effects for district-years and country-months. Note these fixed effects prohibit the identification of the constitutive terms $\mathsf{time\ to\ election}_{mc}$ and ethno-political polarization because the respective variables do not vary within country-months and district-years, respectively. Importantly however, the interaction term of interest, $\mathsf{time\ to\ election}_{mc} \times \mathsf{ethno\text{-}political\ polarization}_{dy}$, remains identified.

The narrow fixed effects serve four purposes. First, as the Arab Spring and common adjournments of electoral contests evidence, elections might be caused or inhibited by violence preceding them. The country-month fixed effects effectively block this link by netting the data of all variation that is constant at the country-month level. Second, they account for omitted variables that are constant at this level and influence both, the timing of elections and the occurrence of riots. These covariates include all national-level socio-economic factors. Third, the use of time-varying data on the spatial extent of districts and the related danger of boundary changes that are endogenous to elections or riots presents the Modifiable Areal Unit Problem in its time-varying form. By using district-year fixed effects, the problem is alleviated insofar, as for each district-year only one stable areal unit is observed and local causes of past changes are controlled for. Fourth, the district-year fixed effects reduce the impact of locally varying spatial- and temporal auto-correlation. They account for the intermediate past of districts-years and their yearly environment and thereby limit the bias spatio-temporal auto-correlation introduces.

To account for temporal auto-correlation, I follow Carter and Signorino (2010) and approximate the decay of riot-risk after a riot as a cubic polynomial of the time since the last event in a district. To model spatial auto-correlation, I add the number of riots in neighboring districts at time $t-1$, $t-2$, and $t-3$ as additional controls to all models.[22] In sum, the spatial lags in combination with the fixed effects successfully reduce the spatial correlation of residual from a Moran's I of the residuals of an empty model of .02 to -.004 (i.e. no spatial correlation of residuals) in the fully specified model.[23] I cluster standard errors on the district-level. Using different levels of clustering such as the region or the country-year, as well as non-parametric spatio-temporal clustering à la Bester et al. (2011) and Conley (1999) does not change the interpretation of the results (Appendix A2.6).

Results

Figure 3 provides a first descriptive test of Hypothesis 1 that ethno-politically polarized districts experience steeper increases in the number of riots prior to majoritarian elections than their non-polarized counterparts. The figure shows that relatively polarized districts see slightly higher numbers of riots during non-election times and, crucially, experience a starker escalation of riots during electoral campaigns than districts with a low level of polarization. Table 1 reports the results of the statistical analysis of this pattern of pre-election violence. The table summarizes the association of pre-election increases in the number of riots with the level of local ethno-political polarization in majoritarian and mixed electoral systems. Models 2 and 3 iteratively introduce fixed effects on the country- and district-levels. Model 4 finally combines country-month and district-year fixed effects for reasons outlined above. Note that with the full set of fixed effects, the constitutive terms of the main interaction term time to election $\times$ ethno-political polarization are not identified.[24]

The results do not only indicate that ethno-politically polarized districts see more

[22]Spatial lags are calculated on the basis of past riot events in a district's and their neighbors current area.

[23]Moran's I is calculated using contiguous neighbors in the same country and months to construct weights matrices

[24]Districts have a constant value of ethno-political polarization within a year, and all districts within the same country and month have the same distance to the next election.

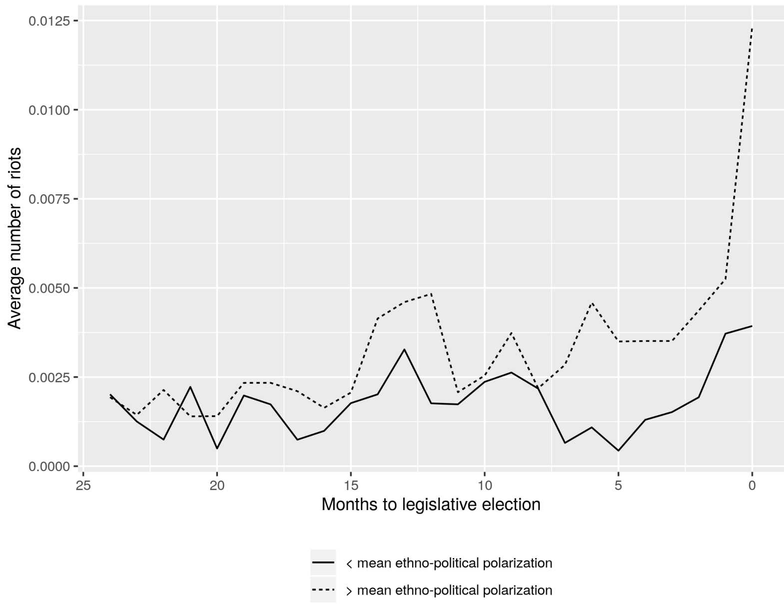


Figure 3: Mean number of riots in polarized and non-polarized districts over the 24 months prior to elections in majoritarian and mixed systems.

riots over the entire period[25] but crucially, that they see a markedly higher increase of rioting preceding elections than non-polarized districts. As evidenced by Figure 4, the substantive effect of ethno-political polarization on pre-election increases in the number of riots is large and precisely estimated.[26] While Model 1 indicates that non-polarized districts see an increase of the average number of riots by a factor of 2.7 over the year preceding a legislative election, the number of riots in polarized districts increases almost twice as much, by a factor of 4.9.[27] Note that, although the average and predicted number of riots per district-month is low, these results imply substantive effects once we take into account the small spatio-temporal size of the units of analysis and aggregate the results up the country-month level. For example, reducing the ethno-political polarization of 775 Nigerian districts from their average of .38 to 0 decreases the number of riots predicted by Model 1 during the legislative election month April 2007 from 4.3 to 1.6.

As a first indication of the robustness of the result, the difference in the local escalation of the number of riots prior to elections seen between polarized and non-polarized districts remains very stable once the country-month and district-year fixed effects are added to the model (Model 4, Table 1). They control for unobserved

[25] See also Montalvo and Reynal-Querol (2005) on ethnic polarization and civil conflict.

[26] Unless otherwise noted, all results reported below are associated with p-values below .05.

[27] All covariates other than time to election and ethno-political polarization are set to their sample mean.

Table 1: Local ethnic polarization & pre-election violence in majoritarian and mixed systems

	Dependent variable:			
	Riots (SCAD)	Riots (SCAD)	Riots (SCAD)	Riots (SCAD)
	(1)	(2)	(3)	(4)
Constant	−0.0003			
	(0.0012)			
Time to election	−0.0386***	−0.0394***	−0.0375***	
	(0.0109)	(0.0111)	(0.0117)	
Ethno-pol. polarization	0.0008**	0.0011***	−0.0011	
	(0.0003)	(0.0004)	(0.0010)	
Time to elec. × Ethno-pol. polar.	0.0079***	0.0078***	0.0072***	0.0076***
	(0.0022)	(0.0022)	(0.0023)	(0.0029)
Population (log)	0.0007***	0.0010***	−0.0008**	
	(0.0001)	(0.0002)	(0.0003)	
Time to elec. × Population	0.0034***	0.0035***	0.0033***	0.0045***
	(0.0009)	(0.0009)	(0.0010)	(0.0015)
Sample:	Maj. & Mix.	Maj. & Mix.	Maj. & Mix.	Maj. & Mix.
Fixed effects:	–	country	district	district-year & country-month
Spatial lag$_{t-1,t-2,t-3}$:	yes	yes	yes	yes
Polynomial DV^{1,2,3}:	yes	yes	yes	yes
Mean DV:	0.0014	0.0014	0.0014	0.0014
Observations	434,303	434,303	434,303	434,303
R^2	0.0054	0.0066	0.0418	0.2311

Notes: OLS linear models. Standard errors clustered on the district-level in parentheses. Significance codes: *p<0.1; **p<0.05; ***p<0.01

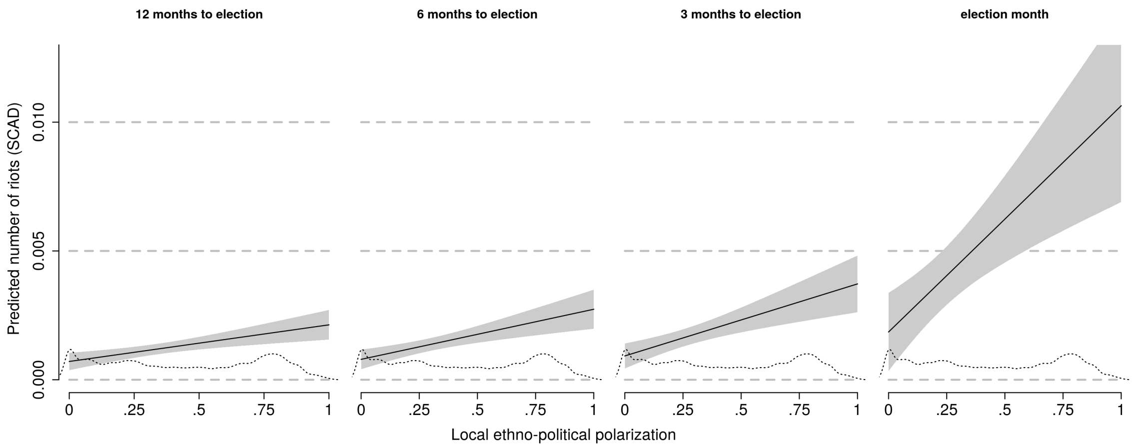


Figure 4: Prediction of the number of riots over the pre-election period in majoritarian polities, varying the degree of local ethno-political polarization.
Note: Based on Model 1 in Table 1. All covariates are held at their sample mean. The dotted line indicates distribution of ethno-political polarization in the sample.

heterogeneity that might influence the timing of elections, spatio-temporal auto-correlation not captured by the respective controls, as well as endogenous changes of district borders.

So far, the baseline results support the argument that, in majoritarian systems, local ethno-political polarization heightens the risk of pre-election increases in the number of riots. Following Hypothesis 2, this finding can only be attributed to the nature of majoritarian systems if no such effect is found in PR elections. To estimate the difference in the effect of local polarization on pre-election increases in the number of riots, I interact all predictors in the baseline model with a PR dummy and extend the sample to all countries in the sample. Furthermore, I extend the range of outcomes with data on riots and riot fatalities retrieved from ACLED which are likely less affected by media bias but only cover the time since 1997 (Raleigh et al., 2010).

Table 2: Local ethnic polarization & pre-election violence: Majoriarian vs. PR elections

	Dependent variable:		
	Riots (SCAD)	Riots (ACLED)	Fatalities (ACLED)
	(1)	(2)	(3)
Time to elec. × Ethno-pol. polar.	0.0076***	0.0086**	0.0112**
	(0.0029)	(0.0041)	(0.0053)
Time to elec. × Population	0.0045***	0.0081***	0.0083***
	(0.0015)	(0.0026)	(0.0030)
Time to elec. × Ethno-pol. polar. × PR	−0.0084***	−0.0137**	−0.0120**
	(0.0030)	(0.0067)	(0.0054)
Time to elec. × Population × PR	−0.0040**	−0.0011	−0.0080***
	(0.0016)	(0.0050)	(0.0030)
Sample:	all	all	all
Spatial lag$_{t-1,t-2,t-3}$:	yes	yes	yes
Polynomial DV^{1,2,3}:	yes	yes	yes
District-year FE:	yes	yes	yes
Country-month FE:	yes	yes	yes
Mean DV:	0.0012	0.0024	0.001
Observations	542,684	394,360	394,360
R^2	0.2323	0.2521	0.1670

Notes: OLS linear models. Standard errors clustered on the district-level in parentheses. Significance codes: *p<0.1; **p<0.05; ***p<0.01

In its first three rows, Figure 5 plots the marginal effect of the interaction of ethno-political polarization × the time to elections under majoritarian and PR rules as estimated in Table 2. In the first column, the results closely mirror the baseline results on the effects of local ethno-political polarization in mixed and majoritarian systems, varying the data on riots between the SCAD and ACLED data. The second columns shows that there is no electoral violence-inducing effect of local ethno-political polarization in PR systems. The respective coefficients are small, negative and statistically insignificant. Finally, the last column in Figure 5 evidences that there is a marked and statistically significant difference in the effects of local ethno-political polarization between the two ideal types of electoral systems.

In sum, these results strongly suggest that the effects of local ethno-political polarization found in majoritarian and mixed systems are due to the nature of majoritarian as compared to PR elections. Local ethno-political competition does not increase the risk of pre-election violence in PR systems.

Robustness checks

In the following, I summarize the results of a number of robustness checks. Figure 5 summarizes the main findings. Appendix A2 presents all analyses in further detail.

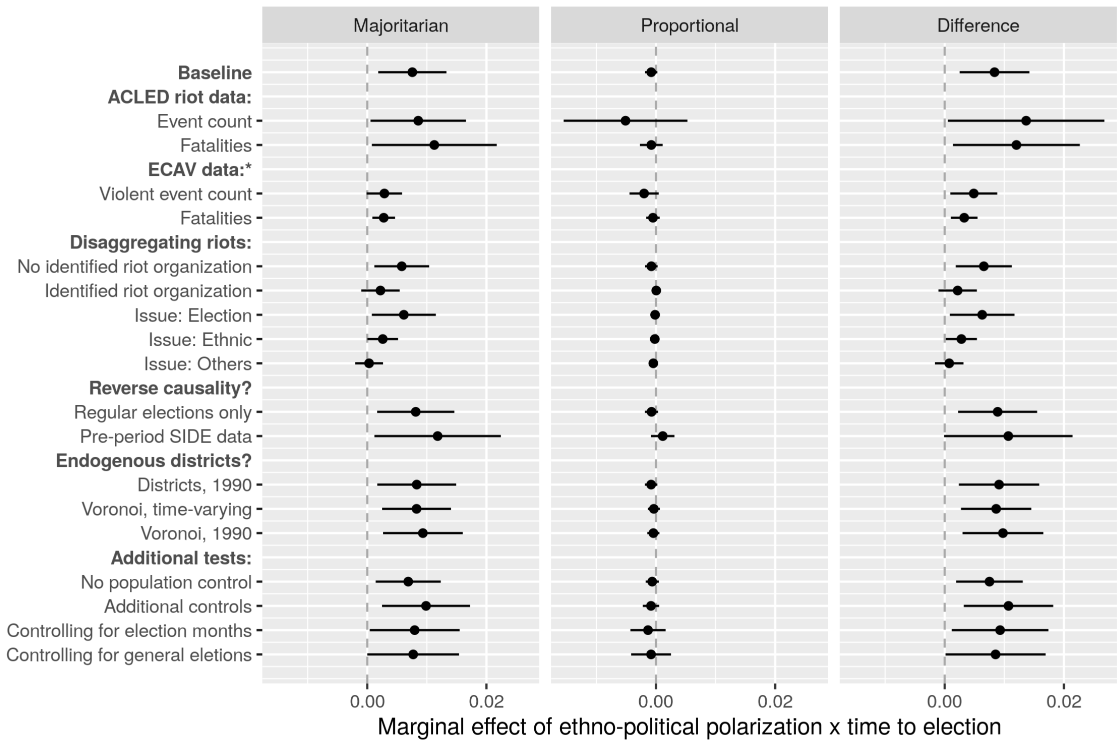


Figure 5: Robustness checks on Model 1 in Table 2 with 95% CIs.
Note that the coefficient in the "ECAV data" section reflect the cross-sectional estimate of the effect of ethno-political polarization. See Appendix A2 for details.

Direct measure of electoral violence: I first address the question whether the results above indeed capture *electoral* violence. An analysis of the 'Electoral Contestation and Violence' (ECAV) data collected by Daxecker et al. (2019) reveals that the number of instances and fatalities of electoral violence during the six month preceding an election significantly increases in ethno-political polarization in majoritarian, but not proportional systems (Table A2). Note that the coverage of the ECAV data is limited to pre-election periods and therefore only allows for a cross-sectional research design.

Disaggregating riots: Disaggregating the SCAD data on rioting, I test whether the results are mainly driven by riots with a clearly identifiable leadership or organization (e.g. political parties or unions) or without. Participants of riots with unidentified leadership or organization are oftentimes identified by 'ethnic' labels.[28] They likely have a broader popular participation and their anonymous perpetrators are harder to punish after the fact. In line with my theoretical argument, I therefore expect that riots coded by SCAD as 'spontaneous' drive the results. In addition, SCAD provides information on the conflict issues mentioned in news articles. Among the mutually non-exclusive issues, I expect "elections" and "ethnic discrimination, ethnic issues" to drive the results. The analysis shows that the effects mostly stems from 'spontaneous' riots, and riots reported to be related to electoral and ethnic, rather than all other issues (see Table A3). Lastly, I find no effects of ethno-political polarization of pre-election increases in the number of local demonstrations, strikes, and violent attacks by militias. Taken together, these results support the argument that ethnic riots are campaign weapons in ethno-politically polarized constituencies.

Reverse causality: Two types of reverse causality may explain the results. In the first, violence directly affects the timing of an election, either causing an early poll or delaying it, thereby biasing the main results. To account for this possibility, I re-estimate the baseline model, using the time to the next *regular* election as coded by NELDA to capture the pre-election increase in rioting. By doing so, I effectively drop all elections that have been held either early or late from the sample thereby precluding them from affecting the estimates. The results on this subset of elections closely corresponds to the main results. The second type of reverse causality may arise if pre-election riots substantively change the subsequent ethnic composition of a district. For 40 percent of the district-months in the main sample, no past or contemporaneous SIDE data is available. Dropping these observation to avoid potential reverse causality slightly *increases* the estimated effect of ethno-political polarization on pre-election rioting in majoritarian settings. However, if

[28] The SCAD data uses the label of 'spontaneous' riots for this type. Importantly, the fact that international media has no information on organizers and instigators does not mean that the respective riots have not been covertly planned and carried out for strategic reasons (e.g. Brass, 2011; Horowitz, 2001; Wilkinson, 2004).

reverse causality would affect the results, the point estimate would drop towards zero. In sum and as discussed in more detail in Appendix A2.4, there is no evidence that reverse causality that affects local ethnic polarization or the timing of elections biases the results.

Endogenous districts: Responding to past or expected violence, politicians might have adjusted district borders to foster peace or to incite conflict. To account for such endogenous borders, I use (1) stable districts as defined in 1990 and (2) artificial districts based on Voronoi tessellations around districts' centroids as alternative units that are less biased by endogenous district designs. The analysis in Appendix A2.5 suggests that the baseline results are, if at all, underestimating the effect of ethno-political polarization on pre-election riots in majoritarian systems.

Additional analyses: I further probe the robustness of the results in Appendix A2.6. I first drop the control for population size, which might bias the results. Second, I add three additional control variables interacted with time to election to account for potential omitted variable bias. In particular, I add districts' pure ethnic polarization, urban population, nightlight emissions, as well as the shares of the ethnically included and irrelevant population as additional controls. Bolstering the confidence in the baseline results, the effects of ethno-political polarization in interaction with the time to majoritarian and PR elections remain stable. Third, the main results might be caused by election months in which I do not distinguish pre- from post-election riots. I therefore add an interaction of ethno-political polarization with a dummy for election months to the model. This does not change the result. Lastly, I disentangle the effects of upcoming presidential and legislative elections that are held concurrently and might therefore exhibit different patterns than 'pure' legislative elections (Wahman and Goldring, 2020). The results suggests statistically indistinguishable effects of ethno-political polarization before general and pure legislative elections.

The fear of pre-election victimization and local ethno-political polarization

As shown above, local ethno-political competition is strongly associated with district-level increases in the number of riots prior to majoritarian and mixed but not PR elections. In the following, I assess the effect of local ethno-political competition on individuals' fear and experience of pre-election violence. This analysis avoids media biases in the riot data (von Borzyskowski and Wahman, 2019; Weidmann, 2016) and provides evidence on the extent of individual-level pre-election vicitimization in polarized constituencies.

Building on Rauschenbach and Paula (2019), I draw on Afrobarometer (2018) surveys rounds 4-6 from 19 countries (Figure A1), which asked individuals: 'During election campaigns in this country, how much do you personally fear becoming a victim of political intimidation or violence?' Additionally, I examine Afrobarometer pre-election surveys from Nigeria (2007) and Uganda (2010/2011) that contain data on whether respondents or their community have been subject to recent campaign threats relating, inter alia, to their physical well-being. While available for only two elections, this is a more accurate measure of electoral violence than individuals' fear of it. While other forms of campaign violence than riots can affect individuals' reports and fear, I expect response patterns to coincide with the main results if pre-election rioting indeed intends to affect voters. Without knowing the immediate cause of individuals' reports and fears, I can however not completely rule out that response patterns are completely driven by non-riot forms of political violence.

I match the district-level measure of ethno-political polarization in the year prior to a survey[29] to Afrobarometer respondents via the geographic location of survey clusters (Ben Yishay, Ariel Rotberg et al., 2017).[30] The main analyses are conducted using the following OLS specification:[31]

$$y_{idct} = \delta_{ct} + \beta_1 \textsf{ethno-political polarization}_{dt} + \delta \boldsymbol{X}_{id} + \epsilon_{id},$$

where outcomes y of an individual i in district d of country c interviewed in year t is regressed on the district's level of ethno-political polarization. I only compare respondents interviewed in the same survey by adding survey fixed effects δ_{ct}. Control variables $\boldsymbol{X}_{id}$ consist of the size of districts' population, as well as respondents' sex, their age and its square, their level of education and a dummy for urban respondents. To compare patterns between majoritarian and proportional systems, I interact all explanatory variables with a dummy for PR systems. Standard errors are clustered on the district-level.[32]

[29]For surveys after 2013, I use the 2013 value. This does not affect the results (Table A16).

[30]For the additional rounds from Uganda and Nigeria, I geocode respondents via the names of districts. See Appendix A3.1.

[31](Ordered) logistic regressions with country-round dummies lead to very similar results (Tables A17 to A18).

[32]For different standard error clusterings, see Table A15.

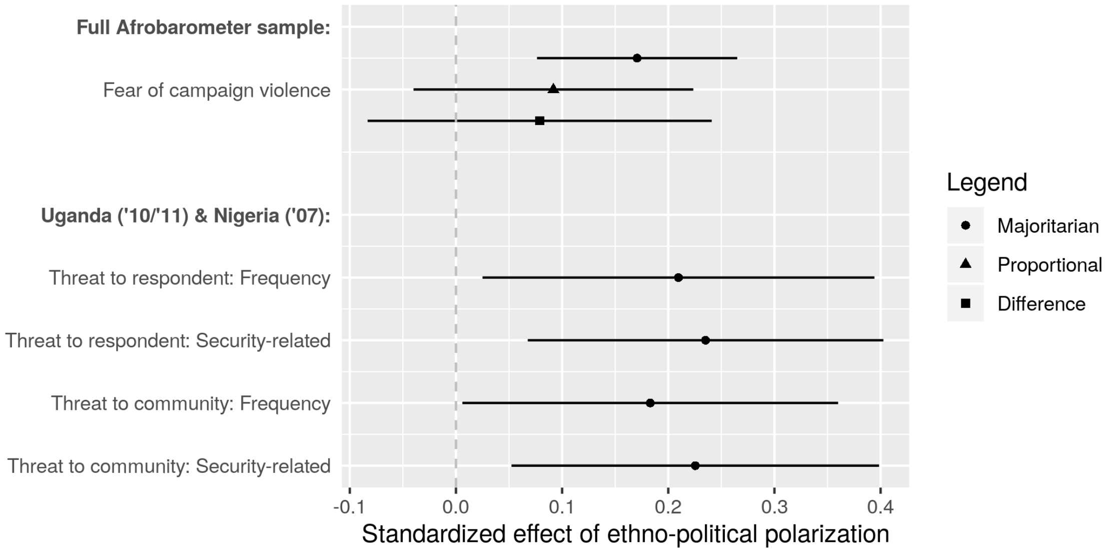


Figure 6: Estimated standardized effect of local ethno-political polarization on fear and experience of pre-election violence.
Note: Effects are measured in standard deviations of the respective outcome variables. The figure plots estimates from Model 3 in Table A12 and from Models 1–4 in Table A13. See Appendix A3.3 for further details.

Results

Figure 6 presents the estimates of the standardized effects of local ethno-political polarization on respondents' fear and experience of campaign violence.

In majoritarian systems, the fear of respondents is positively and significantly associated with the ethno-political polarization of their home district. The effect, plotted in the first row of the graph, amounts to a change in the reported level of fear by 0.2 standard deviations as one moves the polarization measure from 0 to 1. This effect of local ethno-political polarization is much weaker in pure proportional systems, though not precisely estimated at zero. The difference between pure PR and majoritarian systems is not statistically significant (p= .34). This stems from the noisy estimate in the PR sample, which features only 352 districts as compared to 1264 in the majoritarian sample. The results are robust to adding additional district levels controls, dropping observations with SIDE data collected after survey interviews, and accounting for factors that may lead to ethnically biased survey responses (Adida et al., 2016, Appendix A3.3).

Moving beyond subjective *perceptions* of fear, Figure 6 reports the estimated effects of ethno-political polarization on reports of electoral threats in Uganda and Nigeria. Respondents in polarized districts in both countries report that they and members of their community have been targeted significantly more often by campaign threats than those living in non-polarized areas. The effect on security-related threats is similarly strong. Respondents who live in polarized areas are on average 5.1 percentage points or .24 standard deviations more likely to have received such a threat. Unsurprisingly, the effect on reports about security-related threats being issued at community members is consistently estimated. In sum, these findings show individuals in ethno-political polarized districts under majoritarian voting experience more electoral violence, thus bolstering the main theoretical argument.

Conclusion

Local political competition between ethnic groups can increase the odds of pre-election violence in majoritarian elections in Africa. By focusing on the nexus between local ethno-political cleavages, the electoral system, and campaign violence, the preceding analysis highlights the importance of socio-political geographies for gauging the merits of majoritarian as compared to proportional electoral systems.

In particular, I argue that majoritarian elections turn violence where ethnic constituencies of similar size compete for legislative seats at the local level. Because competition in proportional systems occurs at higher geographical level, local ethno-political polarization has no effect on violence before PR elections. This argument is supported by results that show that the level of violence before majoritarian elections significantly increases in the local level of ethno-political polarization. Similarly, citizens who live in polarized districts in majoritarian polities systematically report substantially higher levels of fear of pre-election violence than their co-nationals living in non-polarized districts do. These patterns of pre-election violence in ethno-politically polarized districts under majoritarian voting do not threaten electoral integrity in pure PR systems.

Echoing arguments made by Barkan et al. (2006) and Wagner and Dreef (2013), these results suggest that constitutional engineers are well advised account for ethnic geographies when drafting electoral institutions. This is particularly important in unconsolidated democracies – in countries with more established norms of peaceful campaigning, local ethnic competition is less likely to lead to widespread violence. The results show that majoritarian elections can turn violent in areas where politically mobilized ethnic groups make up roughly equal shares of the population, thus increasing electoral competition along ethnic lines. The contrasting finding of an absence of this pattern in PR elections adds more detail to our understanding of the origins of the general propensity of more severe electoral violence in majoritarian than proportional elections (Birch, 2007; Fjelde and Höglund, 2016).

In addition to the contrast between majoritarian and PR elections, the findings highlight the potential for district designs in majoritarian systems that reduce district-level ethno-political polarization and electoral violence. However, the likely positive effects of such district designs must be discussed alongside their impact on the competitiveness of elections, the translation of votes to seats, as well as the representativeness of future electoral results. Furthermore, districts designed to achieve non-polarized ethnic compositions may well legitimize “ethnic gerrymandering” more generally, further politicize ethnic identities, and ultimately foster ethnic conflict. While the immediate effect of district-level polarization on electoral violence shown in this paper can inform such discussions, it should be only one of many concerns addressed by electoral designs. These should be ultimately geared towards serving citizens’ preferences.

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Local Ethno-Political Polarization and Election Violence in Majoritarian vs. Proportional Systems

ONLINE APPENDIX

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A1 Data overview

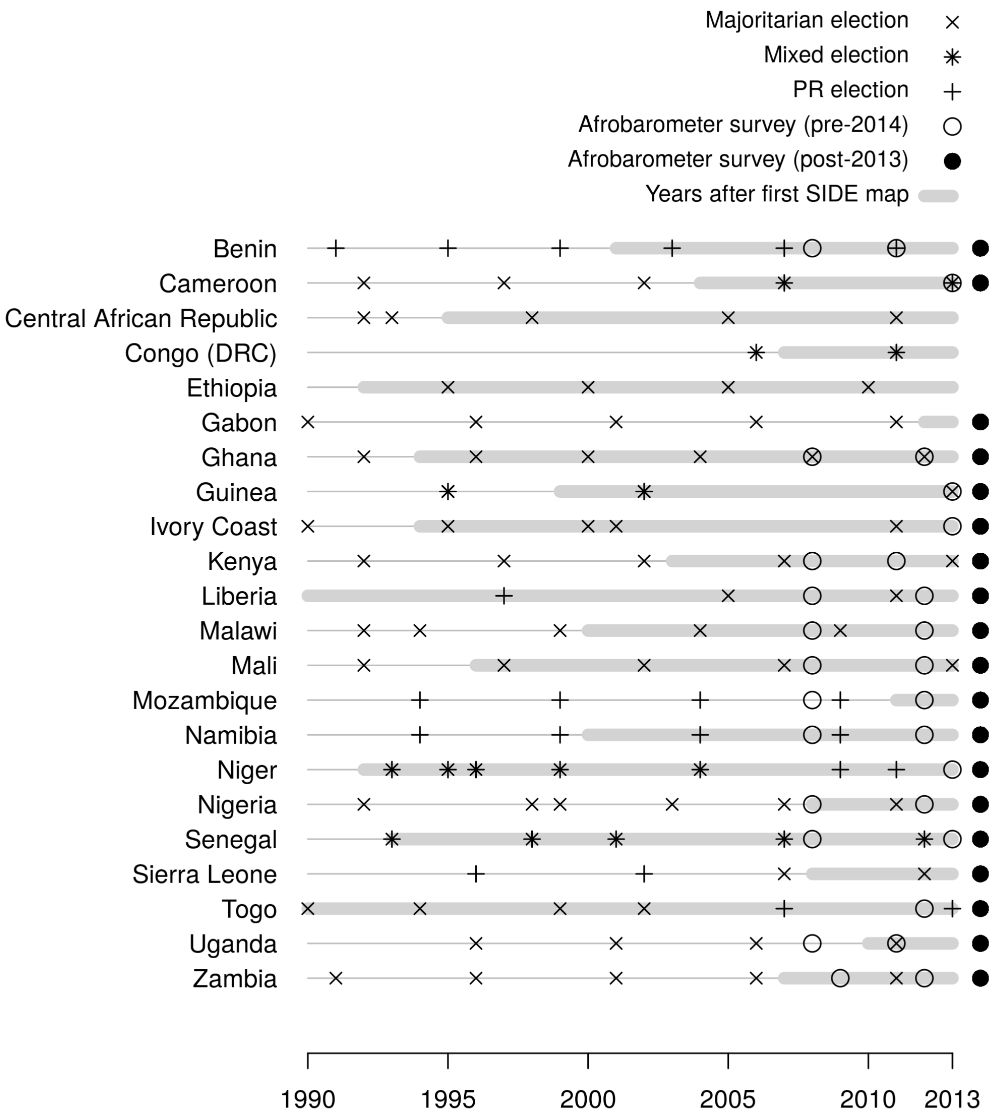


Figure A1: Summary of the samples used in the empirical analyses.

A2 District-month analysis

A2.1 Summary statistics

Table A1: Summary statistics: Districts 1990–2013

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Time to election	547,577	0.092	0.163	0.016	0.024	0.077	1.000
Ethno-pol. polarization	547,577	0.462	0.295	0.000	0.198	0.741	1.000
Population (log)	547,577	11.468	1.270	3.086	10.958	12.208	15.452
Ethnic polarization	547,577	0.567	0.184	0.000	0.417	0.712	0.954
Urban population (log)	547,577	5.610	5.187	0.000	0.000	10.353	15.440
Nightlights per capita	503,532	0.013	0.146	0.000	0.0001	0.006	8.542
Riots (SCAD; log)	547,577	0.001	0.030	0	0	0	2
Riots (ACLED; log)	394,360	0.002	0.047	0.000	0.000	0.000	2.639
Fatalities (ACLED; log)	394,360	0.001	0.046	0.000	0.000	0.000	6.909
Viol. events (ECAV; log)	68,551	0.004	0.067	0.000	0.000	0.000	2.996
Fatalities (ECAV; log)	68,551	0.002	0.053	0.000	0.000	0.000	4.727
Majoritarian & mixed	547,577	0.801	0.399	0	1	1	1
PR (pure)	547,577	0.199	0.399	0	0	0	1

A2.2 Direct measures of electoral violence

Table A2 presents the results of the analyses of violent events of electoral violence as coded by Daxecker et al. (2019). These events are coded only for the six months preceding elections. It is therefore impossible to model the *increase* in violence as districts move from between-election to campaign periods. For this reason, the models draw on cross-sectional variation between polarized and non-polarized districts in the six months before legislative elections and do not model the increase of violence. The events coded by the data include only events that coders attribute to the election. This might introduce under-counting and/or bias if violent events, which have been planned with electoral motives in mind are not described as such in the news articles the data relies on.

The results show that ethno-politically polarized districts see more violent and election-related events in the six months before legislative elections in majoritarian countries (Model 1, $p < .1$). As evidenced by the negative and statistically significant interaction term of polarization × PR in Model 2, this relationship is absent in pure PR systems. While the coefficient of the effect of ethno-political polarization on the count of all violent events is associated with somewhat higher levels of uncertainty, standard errors are much smaller once we move to the count of victims in Models 3 and 4.[1] Substantively more people die from pre-election violence in polarized

[1] ECAV only offers ordinal estimates for the number of victims. To derive a sum of fatalities in a district-month, I take the sum of the lowest number of victims in a given fatality-bracket coded by ECAV (e.g. 10 for the bracket that ranges from 10 to 100 victims).

districts under majoritarian voting than in non-polarized ones. Again, this pattern is absent in PR systems.

Table A2: Local ethnic polarization & pre-election violence from ECAV

	Dependent variable:			
	Violent Events (ECAV)	Violent Events (ECAV)	Fatalities (ECAV)	Fatalities (ECAV)
	(1)	(2)	(3)	(4)
Ethno-pol. polarization	0.0026*	0.0029*	0.0027***	0.0028***
	(0.0015)	(0.0015)	(0.0010)	(0.0010)
Population (log)	0.0026***	0.0028***	0.0019***	0.0020***
	(0.0007)	(0.0007)	(0.0004)	(0.0005)
Ethno-pol. polarization × PR		−0.0049**		−0.0033***
		(0.0020)		(0.0011)
Population (log) × PR		−0.0027***		−0.0020***
		(0.0011)		(0.0006)
Sample:	Maj. & Mix.	all	Maj. & Mix.	all
Spatial lag$_{t-1,t-2,t-3}$:	yes	yes	yes	yes
Polynomial DV^{1,2,3}:	yes	yes	yes	yes
District-year FE:	no	no	no	no
Country-month FE:	yes	yes	yes	yes
Mean DV:	0.0049	0.0042	0.0022	0.0019
Observations	56,236	68,488	56,236	68,488
R^2	0.1134	0.1101	0.0775	0.0802

Notes: OLS linear models. Standard errors clustered on the district-level in parentheses. Significance codes: *p<0.1; **p<0.05; ***p<0.01

A2.3 Disaggregating the SCAD riot data

Analysis by riot type: I here test whether the results are mainly driven by riots with or without an identified leadership or organization according to the SCAD data.[2] Ethnic riots are most often coded as riots without clear organization, with participants identified by 'ethnic' labels. Other types of participants of such riots include "angry mobs" or unidentified crowds of "supporters of" politicians. In comparison, riots with a leadership or organization identified by the news sources of SCAD name political parties or unions as actors. I thus take riots with a non-identified organization as having a broader popular participation and their perpetrators are harder to punish after the fact. In line with my theoretical argument, I therefore expect the results to be driven by such riots.

[2]These labels correspond to SCAD's coding of 'organized' vs. 'spontaneous' riots, which I take as slightly misleading since the information used to code these labels does not relate to the question whether a riot broke out "spontaneously". In fact, consistent case study evidence suggests that many appearingly spontaneous riots are well planned and organized for strategic reasons (e.g. Brass, 2011; Horowitz, 2001; Wilkinson, 2004).

In addition, SCAD provides information on the three most important conflict issues mentioned in news article, ranging from elections, via 'ethnic' issues, the economy, education, to human rights and 'pro-government'. Among these mutually non-exclusive issues, I expect particularly "elections" and "ethnic discrimination, ethnic issues" to drive the results. I count the respective number of riots for both issues, as well as a third variable that captures the number of riots per district month that is attributed to neither of the two issues.

The resulting analyses are reported in Table A3. The coefficients show that that the effects in the baseline model mostly stem from riots without an identified organization (Model 1) as compared to those with an identified organization, which see less of an pre-election increase that is correlated with local ethno-political polarization (Model 2). Furthermore, the results are mostly driven by riots reported to be related to electoral and ethnic issues (Models 3 and 4). The coefficient of interest in the model of rioting around all other issues is estimated to be close to zero and statistically insignificant (Model 5). In all, these findings support the theoretical argument in that the predicted type of riot drives the results.

Table A3: Local ethnic polarization & various types of pre-election riots

	Dependent variable:				
	Riot organization		Riot issue		
	Not identified	Identified	Elections	Ethnic	All others
	(1)	(2)	(3)	(4)	(5)
Time to elec. × Ethno-pol. polar.	0.0058**	0.0022	0.0061**	0.0026**	0.0003
	(0.0023)	(0.0016)	(0.0027)	(0.0013)	(0.0012)
Time to elec. × Population	0.0032**	0.0015**	0.0046***	0.0014***	−0.0003
	(0.0013)	(0.0007)	(0.0016)	(0.0005)	(0.0005)
Time to elec. × Ethno-pol. polar. × PR	−0.0066***	−0.0022	−0.0063**	−0.0028**	−0.0008
	(0.0024)	(0.0016)	(0.0028)	(0.0013)	(0.0012)
Time to elec. × Population × PR	−0.0026*	−0.0015**	−0.0042***	−0.0015***	0.0004
	(0.0014)	(0.0007)	(0.0016)	(0.0005)	(0.0006)
Sample:	all	all	all	all	all
District-year FE:	yes	yes	yes	yes	yes
Country-month FE:	yes	yes	yes	yes	yes
Spatial lag$_{t-1,t-2,t-3}$:	yes	yes	yes	yes	yes
Polynomial DV^{1,2,3}:	yes	yes	yes	yes	yes
Mean DV:	0.001	2e-04	2e-04	2e-04	8e-04
Observations	542,684	456,457	542,684	542,684	542,684
R^2	0.2280	0.1982	0.2030	0.1976	0.2246

Notes: OLS linear models. Standard errors clustered on the district-level in parentheses. Significance codes: *p<0.1; **p<0.05; ***p<0.01

Non-riot forms of violence: In addition, Table A4 present the results on using all other types of violence coded in the SCAD data as an outcome. This is to distinguish pre-election rioting from other forms of violence. As explained in the theoretical part, I expect riots rather than other forms of violence to be most used in ethnically contested campaigns. This is because rioting combines the mobilization of one's supporters with the demobilization of the adversary. More organized forms of violence conducted by militias, or non-violent events such as demonstrations and strikes does not have these properties.

The placebo test has the additional advantage of acting as a test of media bias. Because elections involve a generally increased focus of international media on a country – and within it on the particularly troublesome areas – the results might be driven by a higher propensity to report on violence in polarized districts prior to an election. Such media bias should however affect reporting of all types of social conflict events.

Using the information from SCAD on non-riot event types, Table A4 thus conducts a 'placebo' test to assess both issues. The results from Models 2–4 indicate that ethno-political polarization before elections is not associated with increases in the number of reported demonstrations, strikes, or militia-related events. This suggests that the there is a distinct logic to the (ethnic) pre-election riots that is distinct from other types of violence and that the results are not driven by biased media reports.

Table A4: Local ethnic polarization & various forms of pre-election violence

	Dependent variable:			
	Riots (SCAD)	Demonstrations (SCAD)	Strikes (SCAD)	Militia (SCAD)
	(1)	(2)	(3)	(4)
Time to elec. × Ethno-pol. polar.	0.0076***	0.0004	−0.0006	−0.0013
	(0.0029)	(0.0018)	(0.0007)	(0.0032)
Time to elec. × Population	0.0045***	−0.0001	−0.0004	0.0012
	(0.0015)	(0.0010)	(0.0005)	(0.0013)
Time to elec. × Ethno-pol. polar. × PR	−0.0084***	0.0003	0.0011	0.0005
	(0.0030)	(0.0030)	(0.0010)	(0.0035)
Time to elec. × Population × PR	−0.0040**	0.0021	−0.0002	−0.0001
	(0.0016)	(0.0026)	(0.0009)	(0.0014)
Sample:	all	all	all	all
District-year FE:	yes	yes	yes	yes
Country-month FE:	yes	yes	yes	yes
Spatial lag$_{t-1,t-2,t-3}$:	yes	yes	yes	yes
Polynomial DV^{1,2,3}:	yes	yes	yes	yes
Mean DV:	0.0012	0.0013	4e-04	0.0018
Observations	542,684	542,684	542,684	380,017
R^2	0.2323	0.2778	0.2009	0.2855

Notes: OLS linear models. Standard errors clustered on the district-level in parentheses. Significance codes: *p<0.1; **p<0.05; ***p<0.01

A2.4 Addressing reverse causality

As laid out in the man analysis, two types of reverse causality may explain the results. In the first, violence directly affects the timing of an election, either causing an early poll or delaying it, thereby biasing the main results. To account for this possibility, I draw on information from the NELDA project on whether a particular election has been held at its schedules point in time. This information is captured in variable "Nelda6" which answers the question "If regular, were these elections early or late relative to the date they were supposed to be held per established procedure?" I only take regular elections that where held neither early nor late as regular elections. I then encode, for each district-month, the time to the next *regular* election to capture the pre-election increase in rioting. By doing so, I effectively drop all elections that have been held irregularly (i.e. after a coup or civil war), or either early or late. This precludes that such irregular elections affect the estimates. Models (1) and (2) in Table A5 report the results for the majoritarian and combined sample respectively. The coefficients of interest are highly statistically significant and slightly larger than those reported at the baseline. This suggests that including irregular elections therein, if at all, biases estimates downwards. This can happen if rioting in polarized areas lead to the adjournment of elections.

The second type of reverse causality may arise if pre-election riots substantively change the subsequent ethnic composition of a district. As the 1991 electoral violence in Kenya which displaced about 300,000 people illustrates, this scenario is not merely theoretical. However, there is no strong ex ante prior in which direction rioting affects polarization. If violence achieves the goals of its instigators to make a district less competitive, it would decrease polarization by asymmetrically displacing one (or more) groups. However, subsequent violent escalation may lead to widespread displacement of members of all local ethnic groups with unclear effects on polarization.

The main problem for the empirical analysis consists in that for about 40 percent of the district-months in the sample, no past or contemporaneous SIDE data is available due to the late introduction of DHS surveys in the respective countries. In these cases, I therefore use data on the "future" ethnic composition to model "past" electoral violence. This opens the door for reverse causality as described above to bias the results. As a remedy, I drop all observations with no pre-period SIDE data available. As shown in Models 3 and 4 in Table A5, doing so slightly *increases* the estimated effect of ethno-political polarization on pre-election rioting in majoritarian settings. However, if reverse causality would affect the results, the point estimate would drop towards zero. The contrast between majoritarian and

PR systems remains robust although affected by slightly more uncertainty, probably because of the smaller sample. In sum, the results of both robustness checks indicate that reverse causality that affects local ethnic polarization or the timing of elections does not bias the results.

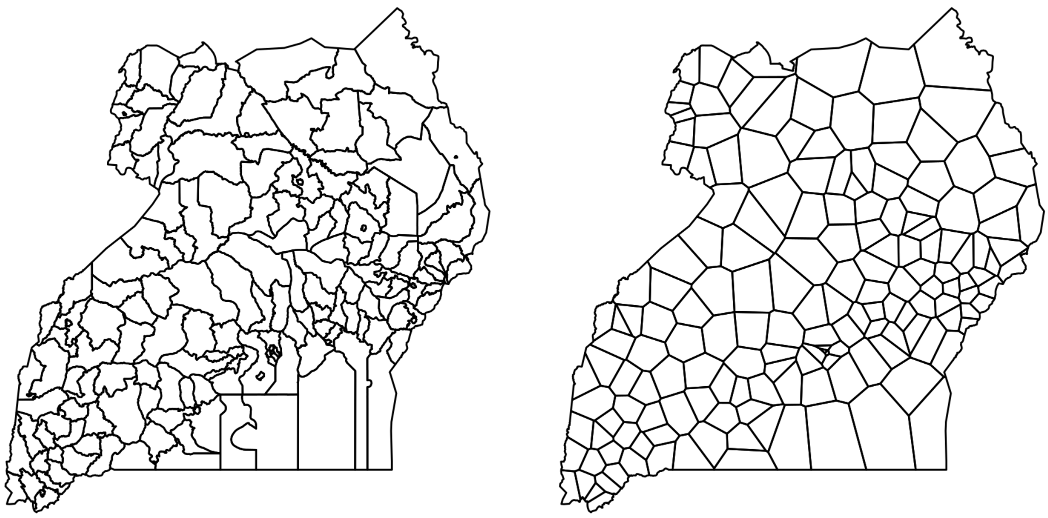
Table A5: Local ethnic polarization and riots (SCAD): Addressing reverse causality

	Regular elections		Pre-period SIDE data	
	Riots (SCAD)	Riots (SCAD)	Riots (SCAD)	Riots (SCAD)
	(1)	(2)	(3)	(4)
Time to reg. elec. × Ethno-pol. polar.	0.0082**	0.0081**		
	(0.0033)	(0.0033)		
Time to reg. elec. × Population	0.0049***	0.0049***		
	(0.0017)	(0.0017)		
Time to reg. elec. × Ethno-pol. polar. × PR		−0.0089***		
		(0.0034)		
Time to reg. elec. × Population × PR		−0.0043**		
		(0.0017)		
Time to elec. × Ethno-pol. polar.			0.0119**	0.0118**
			(0.0054)	(0.0054)
Time to elec. × Population			0.0075***	0.0075***
			(0.0026)	(0.0026)
Time to elec. × Ethno-pol. polar. × PR				−0.0107*
				(0.0055)
Time to elec. × Population × PR				−0.0064**
				(0.0028)
Sample:	all	all	all	all
District-year FE:	yes	yes	yes	yes
Country-month FE:	yes	yes	yes	yes
Spatial lag$_{t-1,t-2,t-3}$:	yes	yes	yes	yes
Polynomial DV^{1,2,3}:	yes	yes	yes	yes
Mean DV:	0.0015	0.0012	0.0015	0.0012
Observations	353,633	449,155	175,298	230,213
R^2	0.2327	0.2341	0.2677	0.2655

Notes: OLS linear models. Standard errors clustered on the district-level in parentheses. Significance codes: *p<0.1; **p<0.05; ***p<0.01

A2.5 Endogenous districts

The experience of past or risk of future local (pre-election) violence might have affected the administrative geography of the countries in my sample. If it is indeed true that local ethno-political polarization increases the risk of violence, peace-seeking politicians might have readjusted district boundaries to create less polarized districts. Other politicians might have used their power to create district that are polarized between ethnic groups they are opposed to. Both dynamics would lead



(a) Observed (b) Voronoi

Figure A2: Observed districts and Voronoi polygons in Uganda 1990.

to district boundaries that are endogenous to pre-election violence and thus bias the results. In order to account for such bias, Table A6 present two strategies in addition to the baseline results of the comparison between majoritarian and PR elections reported in Model 1. First, Model 2 re-estimates the main model with districts as defined in 1990 as the unit of analysis, pretending that they have never changed. Since most countries in Africa introduced competitive legislative elections after that time, I assume the respective districts to be least affected by pre-election violence. Second, to account for further endogenous determinants of district boundaries, I compute Voronoi polygons around the centroids of districts observed in every year from 1990 to 2013 (Model 3) and those observed only in 1990 (Model 4). An example of such Voronoi 'districts' is mapped in Figure A2. The main advantage of these artificial units is that they keep the number and spatial distribution of districts constant while straightening their borders. The units thus account for endogenous district boundaries drawn as a response to past or future violence. For each of these alternative sets of units of analysis I compute the full dataset complete with units' monthly counts of riots, level of ethno-political polarization, population count, etc. Re-estimating the baseline specification with the full set of fixed effects, Table A6 shows that the baseline results are, if at all, underestimating the effect of local ethno-political polarization on the increase in the number of riots before majoritarian elections. The respective coefficients are larger in size than in the baseline results and statistically significant. The results show no effect of ethno-political polarization on increases in rioting before PR elections.

Table A6: Local ethnic polarization & pre-election violence: Varying units of analysis

	Dependent variable:			
	Riots (SCAD)	Riots (SCAD)	Riots (SCAD)	Riots (SCAD)
	(1)	(2)	(3)	(4)
Time to elec. × Ethno-pol. polar.	0.0076***	0.0083**	0.0083***	0.0093***
	(0.0029)	(0.0034)	(0.0029)	(0.0034)
Time to elec. × Population	0.0045***	0.0047***	0.0066***	0.0064***
	(0.0015)	(0.0016)	(0.0018)	(0.0019)
Time to elec. × Ethno-pol. polar. × PR	−0.0084***	−0.0091***	−0.0086***	−0.0098***
	(0.0030)	(0.0034)	(0.0030)	(0.0035)
Time to elec. × Population × PR	−0.0040**	−0.0041***	−0.0059***	−0.0056***
	(0.0016)	(0.0016)	(0.0018)	(0.0019)
Units:	District time-variant	District 1990	Voronoi time-variant	Voronoi 1990
Sample:	all	all	all	all
Spatial lag$_{t-1,t-2,t-3}$:	yes	yes	yes	yes
Polynomial DV^{1,2,3}:	yes	yes	yes	yes
District-year FE:	yes	yes	yes	yes
Country-month FE:	yes	yes	yes	yes
Mean DV:	0.0012	0.0013	0.0012	0.0012
Observations	542,684	517,845	543,951	520,781
R^2	0.2323	0.2342	0.2324	0.2352

Notes: OLS linear models. Standard errors clustered on the district-level in parentheses. Significance codes: *p<0.1; **p<0.05; ***p<0.01

A2.6 Additional analyses

Dropping the population control: Table A7 presents the results of additional robustness checks. Model 1 shows that dropping the control for the size of the local population in interaction with the time to the next election does not affect the results.

Dropping and adding covariates: Model 2 adds a vector of additional control variables that miht either be omitted variables or capture a theoretical mechanisms that is different from the one hypothesized in the main paper *First,* pure *ethnic* polarization rather than *ethno-political* polarization might drive the results. I thus add the local ethnic polarization index calculated directly from the SIDE data. *Second,* the size of districts' population might imperfectly control for local ethnic diversity in urban centers, which also experience substantial pre-election violence. I therefore add a measure of the logged size of districts' urban population from CIESIN et al. (2011).[3] *Third,* ethnic polarization might decrease local development and thereby increase the odds of campaign violence.[4] To account for this alternative pathway, I

[3] Geo-coded urban population counts come from the GRUMP data .

[4] The literature arguing that poverty increases the odds of violent conflict is large, cf. Collier and Hoeffler (2004); Fearon and Laitin (2003). However, in contrast to country-level evidence

add the logged per-capita nightlight emissions (National Geophysical Data Center, 2014) of a district-year as a proxy for economic activity (Chen and Nordhaus, 2011). *Fourth,* the level of ethno-political polarization might be affected by the local level of ethnic exclusion from the national government, which can increase the odds of electoral violence (Brosché et al., 2020; Fjelde and Höglund, 2016). I therefore draw on the match between the SIDE data and the Ethnic Power Relations data (Vogt et al., 2015) and calculate the share of the local population that is part of a politically relevant ethnic group and excluded from executive power. *Fifth* and lastly, the level of polarization between politically relevant ethnic groups might capture the effects of greater or smaller shares of the population being members of politically relevant ethnic groups. I thus include the share of the relevant population in a district in interaction with the time to the next election, again drawing on the EPR data.

Model 2 in Table A7 shows that of these additional variables only the proportion of the urban population has a substantive (and positive) effect on the increase of rioting before elections. Bolstering the confidence in the baseline results, the estimated effect of ethno-political polarization increases.

Accounting for election months: Model 3 in Table A7 adds an interaction of an election-month dummy with the level of ethno–political polarization to gauge whether the effects of the time to election are driven by election months for which one cannot distinguish pre- from post-election violence. The results show that this is not the case.

Alignment with presidential elections: Legislative elections that are aligned and non-aligned with presidential elections might come with different forms of pre-election violence. In particular, the main results might be driven by presidential, rather than legislative contests held at the same time. Distinguishing between general and pure legislative elections,[5] Model 4 in Table A7 re-estimates the baseline analyses, including an interaction term of a general election dummy with the two main variables of inters. The results show that higher levels of ethno-political polarization are associated with steeper increases in the number of riots before legislative elections in majoritarian but not PR systems no matter whether an elections in majoritarian systems are held as general elections or not. The respective interaction

(Alesina et al., 1999; Montalvo and Reynal-Querol, 2005), local level evidence points in the opposite direction (Gerring et al., 2015).

[5]Elections are coded as general elections if a legislative election is accompanied by a presidential one in the same month.

Table A7: Additional robustness Checks: Local ethnic polarization & pre-election riots

	Dependent variable:			
	Riots (SCAD)	Riots (SCAD)	Riots (SCAD)	Riots (SCAD)
	(1)	(2)	(3)	(4)
Time to elec. × Ethno-pol. polar.	0.0069**	0.0099***	0.0080**	0.0077**
	(0.0028)	(0.0038)	(0.0038)	(0.0039)
Time to elec. × Population		0.0044***	0.0045***	0.0055***
		(0.0016)	(0.0015)	(0.0017)
Time to elec. × Ethno-pol. polar. × PR	−0.0075***	−0.0107***	−0.0093**	−0.0085**
	(0.0029)	(0.0038)	(0.0041)	(0.0043)
Time to elec. × Population × PR		−0.0037**	−0.0040**	−0.0050***
		(0.0016)	(0.0016)	(0.0017)
Time to elec. × Ethnic polar.		−0.0017		
		(0.0050)		
Time to elec. × Light p.c.		−0.0014		
		(0.0024)		
Time to elec. × Urban pop.		0.0003**		
		(0.0001)		
Time to elec. × Ethn. excluded		0.0038		
		(0.0043)		
Time to elec. × Ethn. irrelevant		−0.0020		
		(0.0026)		
Time to elec. × Ethnic polar. × PR		0.0020		
		(0.0050)		
Time to elec. × Light p.c. × PR		0.0025		
		(0.0027)		
Time to elec. × Urban pop. × PR		−0.0002*		
		(0.0001)		
Time to elec. × Ethn. excluded × PR		−0.0044		
		(0.0045)		
Time to elec. × Ethn. irrelevant × PR		0.0022		
		(0.0027)		
Election month × EPP			−0.0004	
			(0.0048)	
Election month × EPP × PR			0.0010	
			(0.0049)	
Time to elec. × EPP × Gen. elec.				0.0001
				(0.0049)
Time to elec. × EPP × PR × Gen. elec.				−0.0002
				(0.0052)
Sample:	all	all	all	all
Spatial lag$_{t-1,t-2,t-3}$:	yes	yes	yes	yes
Polynomial DV^{1,2,3}:	yes	yes	yes	yes
District-year FE:	yes	yes	yes	yes
Country-month FE:	yes	yes	yes	yes
Mean DV:	0.0012	0.0012	0.0012	0.0012
Observations	542,684	503,532	542,684	506,510
R^2	0.2320	0.2341	0.2323	0.2324

Notes: OLS linear models. EPP stands for ethno-political polarization. Standard errors clustered on the district-level in parentheses. Significance codes: *p<0.1; **p<0.05; ***p<0.01

terms that account for the difference between pure legislative and general elections are small and statistically insignificant.

Standard error specifications: To gauge whether the results are sensitive to the manner of clustering standard errors, Table A8 presents four variations which increase the level on which errors are clustered. First, I present the baseline model with errors clustered on the district level. Model 2 uses Conley's standard errors which account for spatial and temporal clustering in a non-parameteric manner (Bester et al., 2011; Conley, 1999). Model 3 clusters on the regional (first-level administrative unit) level, and Model 4 on the country-year level.[6] The analyses show that the results are insensitive to the kind of standard error clustering applied, with the Conley clustering even reducing the uncertainty attributed to the estimates.

Table A8: Local ethnic polarization & pre-election violence: Standard error specifications

	Dependent variable:			
	Riots (SCAD)	Riots (SCAD)	Riots (SCAD)	Riots (SCAD)
	(1)	(2)	(3)	(4)
Time to elec. × Ethno-pol. polar.	0.0076***	0.0076***	0.0076**	0.0076**
	(0.0029)	(0.0027)	(0.0031)	(0.0032)
Time to elec. × Population	0.0045***	0.0045***	0.0045***	0.0045***
	(0.0015)	(0.0013)	(0.0016)	(0.0017)
Time to elec. × Ethno-pol. polar. × PR	−0.0084***	−0.0084***	−0.0084***	−0.0084**
	(0.0030)	(0.0028)	(0.0032)	(0.0032)
Time to elec. × Population × PR	−0.0040**	−0.0040***	−0.0040**	−0.0040**
	(0.0016)	(0.0013)	(0.0016)	(0.0017)
SE clustering:	District	Conley	Region	Country-year
Sample:	all	all	all	all
District-year FE:	yes	yes	yes	yes
Country-month FE:	yes	yes	yes	yes
Spatial lag$_{t-1,t-2,t-3}$:	yes	yes	yes	yes
Polynomial DV^{1,2,3}:	yes	yes	yes	yes
Mean DV:	0.0012	0.0012	0.0012	0.0012
Observations	542,684	542,684	542,684	542,684
R^2	0.2323	0.2323	0.2323	0.2323

Notes: OLS linear models. Significance codes: *p<0.1; **p<0.05; ***p<0.01

Constituency-level evidence from Kenya: As discussed in the main paper, the choice of administrative *districts*, although facilitating the comparison of majoritarian and PR systems, might be inadequate for capturing the dynamics of electoral competition in majoritarian systems. Using maps of electoral constituencies from Kenya, Table A9 shows that the results remain comparable once the geographical

[6] Clustering on the country-level would lead to an insufficiently low number of clusters.

unit of analysis is changed to constituencies in which the actual competition for votes takes place. Using the baseline model that includes country-month and district-year fixed effects, all results point towards a positive effect of ethno-political polarization on pre-election violence in Kenya. The respective constituency-level analysis is about three times smaller than that from the district-level analysis. This difference is directly related to the three times lower average number of riots observed in constituencies, which in turn mirrors the fact that each district contains about three constituencies. Given these results and the high correlation between the district- and constituency-level measures of ethno-political polarization (see Figure 1 in the main paper), it seems very unlikely that the results are a mere artifact of the choice of unit of analysis.

Table A9: Local ethnic polarization & various forms of pre-election violence: Kenya constituencies

	Dependent variable:					
	Riots (SCAD)	Riots (SCAD)	Riots (ACLED)	Riots (ACLED)	Fatalities (ACLED)	Fatalities (ACLED)
	(1)	(2)	(3)	(4)	(5)	(6)
Time to elec. × Ethno-pol. polar.	0.0321*	0.1141*	0.1690***	0.3842***	0.1747**	0.6102***
	(0.0185)	(0.0625)	(0.0527)	(0.1369)	(0.0751)	(0.2144)
Time to elec. × Population	0.0069	0.0273	0.0275*	0.0716**	0.0274	0.1042**
	(0.0046)	(0.0177)	(0.0150)	(0.0324)	(0.0186)	(0.0499)
Sample:	Kenya constituencies	Kenya districts	Kenya constituencies	Kenya districts	Kenya constituencies	Kenya districts
District-year FE:	yes	yes	yes	yes	yes	yes
Country-month FE:	yes	yes	yes	yes	yes	yes
Spatial lag$_{t-1,t-2,t-3}$:	yes	yes	yes	yes	yes	yes
Polynomial DV^{1,2,3}:	yes	yes	yes	yes	yes	yes
Mean DV:	0.0017	0.0053	0.0064	0.0173	0.002	0.0055
Observations	57,814	19,220	40,723	14,090	40,723	14,090
R^2	0.2427	0.2819	0.2441	0.3407	0.1417	0.2362

Notes: OLS linear models. Standard errors clustered on the district-level in parentheses. Significance codes: *p<0.1; **p<0.05; ***p<0.01

A3 Evidence from the Afrobarometer

A3.1 Geocoding Afrobarometer for Nigeria (3.5) and Uganda (4.5)

Since its 3rd round, Afrobarometer has coded the 'district' of respondents. However, depending on the country and the respective round, the Afrobarometer districts refer to administrative units on different levels. Most of the time, they can be matched to level-2 units, but sometimes only to lower or higher levels. In order to geographically locate the respondents of the additional rounds of the Afrobarometer conducted in Uganda (round 4.5, 2010/2011) and Nigeria (round 3.5, 2007), I implement a geographical matching procedure consisting of the following steps, each using cleaned ASCII strings as an input. Each step is implemented on those Afrobarometer districts that have not been matched in the previous steps. Districts are only matched within their countries.

1. Match districts to 2nd-level administrative unit names as indicated in the GAUL data of the respective year (FAO, 2014). Fuzzy string-matching using the a maximum Jaro-Winker distance (Winkler, 1990) of 0.1.

2. Match Afrobarometer regions to 1st-level administrative unit names as indicated in the GAUL data of the respective year (FAO, 2014). Fuzzy string-matching using a maximum Jaro-Winker distance of 0.1.

3. Search the `geonames.org` API to access the coordinates of an Afrobarometer district using a maximum Jaro-Winker distance of 0.1. If multiple coordinates are returned, the one with the 1st-level administrative unit name closest to the one indicated by Afrobarometer is chosen.

4. Search the Google Maps API for the Afrobarometer district nested within its region as indicated by the survey. This second parameter has to be specified since no string-distance parameter can be passed to the database. Results are only kept if they indicate that the engine has found a place at a level below the respective 1st-level administrative unit.

The coordinates returned in step 3 and 4 are then mapped to level-2 administrative units from a given survey year, again using the GAUL data (FAO, 2014).

A3.2 Summary statistics

Table A10: Summary statistics: Afrobarometer, rounds 4-6

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Fear of elec. violence	53,212	1.052	1.164	0.000	0.000	2.000	3.000
Ethno-pol. polarization	54,119	0.356	0.330	0.000	0.000	0.693	1.000
Majoritarian & mixed	54,119	0.781	0.414	0	1	1	1
PR (pure)	54,119	0.219	0.414	0	0	0	1
Population (log)	54,119	11.985	1.284	6.526	11.356	12.821	14.937
Urban	53,864	0.622	0.485	0.000	0.000	1.000	1.000
Female	54,119	0.500	0.500	0	0	1	1
Age	53,554	35.524	13.828	18.000	25.000	43.000	105.000
Education	54,002	2.386	0.958	1.000	2.000	3.000	4.000
Same language as interviewer	54,119	0.413	0.492	0	0	1	1
Others checked during interview	54,080	0.045	0.206	0.000	0.000	0.000	1.000
Others influenced	54,047	0.038	0.191	0.000	0.000	0.000	1.000
Others present	54,027	0.322	0.467	0.000	0.000	1.000	1.000

Table A11: Summary statistics: Afrobarometer, Nigeria (3.5) & Uganda (4.5)

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Personal threat: frequency	6,138	0.133	0.502	0.000	0.000	0.000	3.000
Personal threat: security	6,138	0.048	0.215	0.000	0.000	0.000	1.000
Community threat: frequency	5,810	0.170	0.563	0.000	0.000	0.000	3.000
Community threat security	5,810	0.060	0.238	0.000	0.000	0.000	1.000
Ethno-pol. polarization	6,305	0.471	0.261	0.0004	0.237	0.701	0.918
Majoritarian & mixed	6,305	1.000	0.000	1	1	1	1
PR (pure)	6,305	0.000	0.000	0	0	0	0
Population (log)	6,305	12.310	0.819	8.030	11.854	12.794	14.029
Urban	6,305	0.270	0.444	0	0	1	1
Female	6,305	1.500	0.500	1	1	2	2
Age	6,254	33.834	12.755	18.000	24.000	40.000	93.000
Education	6,279	2.571	0.927	1.000	2.000	3.000	4.000
Same language as interviewer	6,305	0.531	0.499	0	0	1	1
Others checked during interview	6,295	0.018	0.133	0.000	0.000	0.000	1.000
Others influenced	6,295	0.013	0.112	0.000	0.000	0.000	1.000
Others present	6,287	0.321	0.467	0.000	0.000	1.000	1.000

A3.3 Survey data: Results and robustness checks

This section presents the robustness checks conducted to gauge the sensitivity of the analysis of the fear of Afrobarometer respondents to fall victim of pre-election violence. Each paragraph provides a short summary of the table that ensues.

Main results on the fear of electoral violence:

Main results from pre-election surveys in Nigeria and Uganda:

Table A12: Local ethnic polarization & fear of pre-election victimization

	Dependent variable:		
	Fear	Fear	Fear
	(1)	(2)	(3)
Ethno-pol. polarization	0.199***	0.107	0.199***
	(0.056)	(0.078)	(0.056)
Ethno-pol. polar. × PR			−0.092
			(0.096)
Sample:	Maj. & Mix.	PR	all
Covariates:	yes	yes	yes
Country-round FE:	yes	yes	yes
Mean DV:	1.1478	0.7189	1.0545
Observations	40,945	11,382	52,327
R^2	0.103	0.054	0.116

Notes: OLS linear models. Control variables include the district population (logged), and urban and female dummy, age and its square, as well as the respondent's education. Model 3 also includes interactions of all covariates with the PR dummy. Standard errors clustered on the district-level in parentheses. Significance codes: *p<0.1; **p<0.05; ***p<0.01

Table A13: Local ethnic polarization & pre-election threats: Nigeria 2007 and Uganda 2010/2011

	Dependent variable:			
	Personal threat: frequency	Personal threat: security	Community threat: frequency	Community threat security
	(1)	(2)	(3)	(4)
Ethno-pol. polarization	0.105**	0.051***	0.103**	0.054**
	(0.047)	(0.018)	(0.051)	(0.021)
Sample:	NIG & UGA	NIG & UGA	NIG & UGA	NIG & UGA
Controls	yes	yes	yes	yes
Country-round FE:	yes	yes	yes	yes
Mean DV:	0.1329	0.0488	0.1697	0.0606
Observations	6,071	6,071	5,745	5,745
R^2	0.011	0.017	0.012	0.020

Notes: OLS linear models. Control variables include the district population (logged), and urban and female dummy, age and its square, as well as the respondent's education. Standard errors clustered on the district-level in parentheses. Significance codes: *p<0.1; **p<0.05; ***p<0.01

Main robustness checks: Table A14 summarizes the main robustness checks discussed in the article. Model 1 summarizes the model in which I add three additional control variables to assess whether the results are driven by pure ethnic polarization, local economic activities captured through nightlight emissions, or the size of the local urban population. While the level of pure ethnic polarization is negatively associated with the fear of pre-election violence and intimidation ($p < .1$),[7] the effect of ethno-political polarization remains stable and significant. Model 2 drops all observations of Afrobarometer respondents that were interviewed before the first SIDE map for their country is available. This does lower the effect of ethno-political polarization but does not change the substantive interpretation of the results. Lastly, Model 3 includes five variables to control for potential bias of the Afrobarometer responses, in particular the co-ethnicity of respondents to their interviewers, dummies for whether others were present, checked with, or influencing the respondent, and lastly a factor of the institutions respondents believe to conduct the survey. The inclusion of these items into the regression model does not change the results.

Table A14: Local ethnic polarization & fear of pre-election victimization

	Dependent variable:		
	Fear	Fear	Fear
	(1)	(2)	(3)
Ethno-pol. polarization	0.224***	0.157***	0.195***
	(0.058)	(0.055)	(0.056)
Ethnic polarization	−0.142		
	(0.088)		
Nightlights/capita (log)	0.009		
	(0.013)		
Urban population (log)	0.0004		
	(0.003)		
Sample:	Maj. & Mix.	Maj. & Mix. & $t \geq t_{SIDE}$	Maj. & Mix.
Covariates	yes	yes	yes
Add. controls			Quality items
Controls	yes	yes	yes
Country-round FE:	yes	yes	yes
Mean DV:	1.1858	1.121	1.1477
Observations	27,590	38,591	40,834
R^2	0.098	0.101	0.106

Notes: OLS linear models. Control variables include the district population (logged), and urban and female dummy, age and its square, as well as the respondent's education. Standard errors clustered on the district-level in parentheses. Significance codes: *p<0.1; **p<0.05; ***p<0.01

[7] Note that this relation turns insignificant when the an ordinal logistical regression is estimated. See Table A18 below.)

Standard error specifications: In parallel to the riot-analysis above, Table A15 presents the results from the survey data analysis with standard erorrs clustered on the district level, Conley's clustered standard errors, and clustering on the regional, and country-survey-round level. While standard errors slightly increase in the level of clustering, all results remain highly statistically significant above the 1% level.

Table A15: Local ethnic polarization & fear of pre-election victimization

	Dependent variable:			
	Fear	Fear	Fear	Fear
	(1)	(2)	(3)	(4)
Ethno-pol. polarization	0.199***	0.199***	0.199***	0.199***
	(0.056)	(0.074)	(0.063)	(0.071)
Cluster-level	District	Conley	Region	Country-round
Sample:	Maj. & Mix.	Maj. & Mix.	Maj. & Mix.	Maj. & Mix.
Controls	yes	yes	yes	yes
Country-round FE:	yes	yes	yes	yes
Mean DV:	1.1478	1.1478	1.1478	1.1478
Observations	40,945	40,945	40,945	40,945
R^2	0.103	0.103	0.103	0.103

Notes: OLS linear models. Control variables include the district population (logged), and urban and female dummy, age and its square, as well as the respondent's education.

Pre-2014 sample: As discussed in the data section of the main paper, the Afrobarometer round 6 was conducted after 2013, the year for which the last data on the political mobilization of ethnic groups is available. Because this relevance barely changes over time, the 2013 data on ethno-political polarization is matched to all respondents interviewed thereafter for the main analyses. Table A16 analyzes whether this coding decision is driving the results. It appears that dropping all observations from after 2013 does not change the results. In majoritarian systems, local ethno-political polarization is significantly associated with the fear of pre-election violence but not so in PR systems. However, the difference between both is not statistically significant.

Table A16: Local ethnic polarization & fear of pre-election victimization: Pre-2014

	Dependent variable:		
	Fear	Fear	Fear
	(1)	(2)	(3)
Ethno-pol. polarization	0.199***	0.111	0.199***
	(0.056)	(0.077)	(0.056)
Ethno-pol. polar. × PR			−0.088
			(0.095)
Sample:	Maj. & Mix.	PR	all
Covariates:	yes	yes	yes
Country-round FE:	yes	yes	yes
Mean DV:	1.1858	0.7321	1.0838
Observations	27,590	8,000	35,590
R^2	0.098	0.046	0.112

Notes: OLS linear models. Control variables include the district population (logged), and urban and female dummy, age and its square, as well as the respondent's education. Model 3 also includes interactions of all covariates with the PR dummy. Standard errors clustered on the district-level in parentheses. Significance codes: *p<0.1; **p<0.05; ***p<0.01

(Ordered) logistic regressions: Lastly, Tables A17 to A19 summarize the results of conducting the main analyses and robustness checks in a logistic rather than the linear regression setup used above. While not as intuitively to interpret, the ordered logit models are a better fit to the outcome indicators. These are ordinal in the case of the fear of pre-election violence and reports of experienced intimidation, and binary for the case of reports of threats of physical safety (see Table A19). However, moving from OLS to ordered logits does not change the substantive conclusions drawn from the Afrobarometer data that fear and reports of pre-election violence is more common in ethno-politically polarized districts in majoritarian, but not PR systems.

Table A17: Local ethno-political polarization and fear: Ordered logit

	(1)	(2)	(3)
	Fear	Fear	Fear
Ethno-pol. polarization	0.299***	0.169	0.301***
	(0.0895)	(0.145)	(0.0900)
Ethno-pol. polarization × PR			−0.135
			(0.169)
Sample	Maj. & Mix.	PR	all
Country-round FE	yes	yes	yes
Controls	yes	yes	yes
Observations	40945	11382	52327
χ^2	1993.3	405.4	2981.7

Notes: Ordered logistical regression models. Control variables include the district population (logged), and urban and female dummy, age and its square, as well as the respondent's education. Model 3 also includes interactions of all covariates with the PR dummy. Standard errors clustered on the district-level in parentheses. Significance codes: $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$

Table A18: Local ethno-political polarization and fear, robustness checks: Ordered logit

	(1) Fear	(2) Fear	(3) Fear
Ethno-pol. polarization	0.344***	0.235***	0.294***
	(0.0920)	(0.0892)	(0.0893)
Nightlights p.c.	0.470		
	(0.647)		
Ethnic polarization	−0.213		
	(0.138)		
Urban population (log)	0.00120		
	(0.00495)		
Sample	Maj. & Mix.	Maj. & Mix. $t \geq t_{SIDE}$	Maj. & Mix.
Add. controls			Quality items
Country-round FE	yes	yes	yes
Controls	yes	yes	yes
Observations	27590	38591	40834
χ^2	1259.5	1925.3	2284.1

Notes: Ordered logistical regression models. Control variables include the district population (logged), and urban and female dummy, age and its square, as well as the respondent's education. Standard errors clustered on the district-level in parentheses.

Table A19: Local ethno-political polarization and pre-election intimidation: (Ordered) logit

	(1) Personal threat: frequency	(2) Personal threat: safety	(3) Community threat frequency	(4) Community threat: safety
Ethno-pol. polarization	0.792**	1.163***	0.752***	1.019***
	(0.371)	(0.394)	(0.291)	(0.341)
Constant		−0.159		0.240
		(1.411)		(1.474)
Sample	NIG & UGA	NIG & UGA	NIG & UGA	NIG & UGA
Model	ologit	logit	ologit	logit
Country-round FE	yes	yes	yes	yes
Controls	yes	yes	yes	yes
Observations	6071	6071	5745	5745
χ^2	35.59	50.92	48.34	71.97

Notes: Ordered logistical regression models. Control variables include the district population (logged), and urban and female dummy, age and its square, as well as the respondent's education. Standard errors clustered on the district-level in parentheses.

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