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August 2015

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August 6, 2015

Abstract

It is often purported that unusually dry conditions provoke riots by intensifying the competition for water. The present paper explores this hypothesis, using data from Sub-Saharan Africa. We rely on monthly data at the cell level (0.5×0.5 degrees), an approach that is tailored to the fact that riots are short-lived and local events. Using a drought index to proxy for deviations of the actual climatic water balance from the normal one, we find that a one-standard-deviation fall in the index (signaling drier conditions) raises the likelihood of a riot in a given cell and month by 8.5 percent. We further observe that the effect of unusual dryness is substantially larger in cells that combine a low supply of blue water with significant agricultural activity, a finding that supports the relevance of the water-competition mechanism.

JEL classification: D74, O13

Keywords: Conflict, riots, water scarcity, disaggregated data

*An earlier version of this paper circulated under the title "Agricultural Shocks and Riots: A Disaggregated Analysis".

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1 Introduction

Water scarcity is often considered to be an important factor behind social conflict and violent clashes in less advanced economies. A typical example of extensive violence over water was observed in 2012 in Kenya, where more than one hundred people died in riots involving farmers and cattle herders (Gleick and Heberger, 2014). This conflict was part of a long-running dispute between the Pokomo people—mostly farmers near the Tana River—and the Orma people, who are seminomadic cattle herders. Back in 2001, at least 130 people were killed in a string of clashes between the same two communities over the access to a river. There is a worry that we will see an increase in the frequency of such sub-national conflicts. For instance, Peter Gleick, president of the Pacific Institute—an institute tracking instances of conflict over water resources—recently stated:[1]

> "I think the risk of conflicts over water is growing—not shrinking—because of increased competition, because of bad management and, ultimately, because of the impacts of climate change. [...] The biggest worry today is sub-national conflicts: conflicts between farmers and cities, between ethnic groups, between pastoralists and farmers in Africa, between upstream users and downstream users on the same river."

This paper empirically investigates the link between unusually dry weather conditions and violent clashes by using geo-referenced data from Sub-Saharan Africa over the 1990-2011 period.[2] Sub-Saharan Africa is particularly vulnerable to unusual dryness: As much as 95% of the crops that are cultivated today are rain-fed, while only 5 percent of all cultivated land is suitable for irrigation (UNEP, 2007). Moreover, according to the United Nations World Water Development Report (UNESCO, 2009), 340 million people lack access to clean drinking water. Consequently, as illustrated by the above example, subnormal levels of rainfall can easily increase resource competition over cropland, pastures, and access to water—and hence induce violent clashes as competing groups start

[1] See *The Guardian* article "Why global water shortages pose threat of terror and war" (Feb 9, 2014).

[2] While the data on violent clashes cover the period from 1990 to 2012, our main explanatory variable—a measure of abnormal water conditions—is only available until 2011.

to fight over a dwindling resource base.

Investigating potential causes of violent clashes, among them water stress, is important for a variety of reasons. *First*, violent clashes—which we will refer to as riots in what follows—are a frequent phenomenon. Our dataset suggests that in the 1990-2011 period Sub-Saharan Africa saw 1,738 events of rioting (compared to 41 civil conflicts or wars, according to the UCDP/PRIO Armed Conflict Dataset). *Second*, riots are often associated with a high number of fatalities. We observe at least one fatality in about 52% of the cases, with a median of 6 and an average of 66 deaths per event. *Finally*, next to the cost in terms of human lives, riots are also costly in economic terms. They disrupt private economic activity and basic government functions; as a result, frequent rioting is a severe obstacle to economic development, particularly in poor places.[3]

Our empirical analysis is based on geographically and temporally disaggregated data. Geographically disaggregated means that we take as units of observation subnational cells of 0.5×0.5 degrees. Temporally disaggregated refers to the fact that we focus on monthly observations. This combination of a very fine temporal and geographical resolution allows us to tackle the specificities of the phenomenon at hand. In particular, our data suggest that riots are short-lived and spatially confined events. Using geo-referenced data from the Social Conflict in Africa Database (SCAD), we see that riots flare up spontaneously and tend to die down quickly: 91% of all riots in our sample do not last for longer than a week. It is further clear that riots are local events: When there is a riot in one cell, 94.3% of neighbouring cells have no incident reported in the same month and 98.2% of neighbouring cells have no incident reported in the preceding month. There is thus no evidence for spatial effects to play a dominant role in our data.[4]

The empirical question we are interested in is how deviations of the actual climatic water balance from normal levels affect the level of rioting in a cell. Following a recent series of papers (among them Harari and La Ferrara, 2014; Couttenier and Soubeyran, 2014),

[3]For anecdotal evidence, see the *Economist* article "A cracked nation holds its breath" (Jan 17, 2008), which describes how the riots that erupted in Kenya in late 2007 imperiled the country's economy.

[4]The finding that riots are spatially confined events is consistent with results in Harari and La Ferrara (2014). Relying on the ACLED database, Harari and La Ferrara do not find any evidence for spatial spillovers in riots (while they do find spillovers in other types of conflict, such as civil conflict or war).

we use a drought index as a proxy for the actual water balance. Our main explanatory variable is the Standardized Precipitation-Evapotranspiration Index (SPEI) constructed by Vicente-Serrano et al. (2010). As the name implies, SPEI is a drought index reflecting the climatic water balance, i.e., the monthly difference between precipitation and potential evapotranspiration. SPEI is expressed in units of standard deviations from the long-run average, so that a positive (negative) value in a given month means an above (below) normal water balance. In addition to SPEI, our main explanatory variable, most specifications include region-by-month, country-by-year, and cell fixed-effects. Therefore, our empirical analysis exploits monthly changes in the (exogenous) water balance in a cell to explain the within-cell variation in local violence.

The raw version of our dataset covers all 0.5×0.5 degree cells in Sub-Saharan Africa. However, riots can hardly occur in sparsely populated zones, in which the formation of crowds with coordinated beliefs is highly unlikely.[5] Our baseline specification thus focuses on a sub-sample of cells with a population above a certain threshold (the 6th decile, evaluated at the country level). We do, however, provide estimates for various alternative thresholds (as well as for the full sample). Our baseline estimates suggest that a one-standard-deviation fall in SPEI increases the likelihood of rioting by 8.5 percent for the average cell in our restricted sample. If we restrict our sample to cells with a population above the 90th percentile, the corresponding number is 25.2 percent.

By using additional cell characteristics, we are able to learn more about the channels through which the actual water balance influences the probability of riots. In particular, we find that a below-normal climatic water balance has a far stronger impact on the level of rioting in cells characterized by a relatively low supply of blue water (i.e., in cells with little underground water and few lakes or rivers). Moreover, the impact on the level of rioting is even stronger in cells that combine a relatively low supply of blue water with significant agricultural activity; and in cells that combine a relatively low supply of blue water with ethnic diversity. So it appears that a negative shock to the climatic water balance has a particularly strong impact in (blue-)water-scarce areas that exhibit substantial

[5]When it comes to individual rioting decisions, coordination in beliefs is important: An agent decides to incur the cost of rioting only if many others are doing so at the same time.

water demand or that host potentially competing groups. These findings support the conjecture—introduced in the beginning—that unusually dry weather conditions breed local violence by triggering competition over scarce water resources. To the best of our knowledge, we are the first to provide evidence for this purported "competition-for-water" mechanism in a large scale empirical study.[6]

When studying the causes of internal conflict, it is important to distinguish between different forms of violence. So far, researches have mainly focused on the impact of weather shocks on internal conflict between organized groups, such as coups, rebellions, or revolutions.[7] However, case-study accounts of conflict related to scarcity of water and land often refer to outbursts of violence between different local communities (based on ethnic or other affiliations), i.e., to riots that take place without explicit state involvement (see, e.g., UNEP, 2007 or Gleick and Heberger, 2014). Contrary to coups or revolutions—where a potentially persistent fight occurs between at least two organized groups over the control of the state—riots are characterized by low requirements regarding organization and funding rather than cohesive actor formation and organized warfare. As a result, riots flare up immediately, are geographically confined, and tend to die down quickly. Our empirical strategy, which is based on a very fine temporal and geographical resolution, is exactly tailored to these characteristics of riots.

This paper is related to a vast empirical literature on the impact of shocks related to weather anomalies on violent conflict (e.g., Miguel et al., 2004; Burke et al., 2009; Ciccone, 2011; Dell et al., 2014; O'Loughlin et al., 2014). By using a temporally and geographically disaggregated empirical strategy, and by relying on a drought index to proxy for weather anomalies, our work has a close link to recent contributions by Theisen et al. (2011), Harari and La Ferrara (2014), Couttenier and Soubeyran (2014), and Hodler and Raschky

[6]Sekhri (2014), using survey data from Indian villages, shows that better access to ground water reduces the number of disputes among farmers over irrigation water. However, neither riots nor the actual climatic water balance play any role in Sekhir's (2014) empirical analysis.

[7]Coups and rebellions are attempts by the armed forces (coup) or by an organized group of civilians (rebellion) to oust the incumbent government. Revolutions, on the other hand, may also lead to a fundamental change in political institutions. According to the usual definition, a conflict between organized groups is called a "civil conflict" if it causes at least 25 battle deaths in a single year and it is called a "civil war" if this number is greater than 1000 (see Blattman and Miguel, 2010).

(2014).[8] However, while all of these papers focus on extensisve and potentially sustained conflicts between organized groups, our focus here is on riots, i.e., on localized events that flare up spontaneously and die down quickly.[9] Consistent with this pattern, our empirical analysis relies on highly disaggregated data, both in terms of space (we focus on cells of 0.5×0.5 degrees) and in terms of time (we use monthly observations). This high level of disaggregation further allows us to shed light on a specific mechanism linking unusual dryness to local violence—competition over scarce resources—that differs from the usual "opportunity-cost-of-fighting" mechanism.

Other papers considering riots include Hendrix and Salehyan (2012) and Aidt and Leon (2014). The former explores whether deviations from normal rainfall patterns increase the likelihood of various types of disruptive events (including incidents of organized and armed violence, but also including spontaneous events like demonstrations, strikes, and riots). Aidt and Leon (2014), on the other hand, focus on the relationship between rioting and democratic transitions. Both papers, however, rely on yearly observations at the country level and do not focus on the mechanism we elicit here.

The rest of this paper is organized as follows. The upcoming section discusses potential linkages between water shocks and riots and explains our empirical strategy. Sections 3 and 4, respectively, describe the dataset and our empirical results. Section 5 concludes.

2 Hypothesis and Empirical Strategy

There exists an extensive literature emphasizing that an unusually dry conditions, potentially in combination with other social factors, can contribute to the outburst of riots (see, e.g., Hendrix and Salehyan, 2012, and the literature cited therein). The main line of argumentation is that unusual dryness may lead to conflict among local consumers of

[8] A complementary literature explores how enduring structural problems (as distinguished from transitory shocks) affect the incidence of conflict. Part of this literature also relies on subnational data from Africa. Examples include Michalopoulos and Papaioannou (2012) who focus on the consequences of ethnic partitioning; and Besley and Reynal-Querol (2014) who explore the role of historical conflicts.

[9] The present focus on water competition and riots is also an important factor distinguishing our study from recent work by Wischnath and Buhaug (2014) who use subnational data from Indian states to explore how fluctuations in food production affect the severity of ongoing conflicts.

water, especially among those who depend on water as an input into production. Water is a major input for agricultural producers and pastoralists, as well as for manufacturing and mining. Unusually dry weather conditions may lead to tougher competition over access to surface water and wells, potentially resulting in an outburst of violence within professional groups (e.g., pastoral conflicts) or between professional groups (e.g., between pastoralists and farmers). Butler and Gates (2012), developing a model of conflicts between pastoralist groups in East Africa, show that such an outcome can be expected in particular if the shock leads to, or amplifies, severe resource asymmetries between competing groups. Moreover, many actual accounts of riots (of which an example is given in the introductory paragraph), as well as theoretical considerations,[10] suggest that the impact of a negative water-balance shock on violence may be amplified by ethnic divisions.

Finally, unusually dry conditions may spark riots by inducing (short-range) migration within a certain geographical region. Gleditsch et al. (2007) point out that such

> "[Environment-induced migration] may lead to social tensions and sporadic violence in receiving areas, but is not likely to cause sustained, organized armed conflict." (p. 4)

Motivated by these arguments, Section 4 explores whether an immediate impact of a negative water-balance shock on sporadic violence—i.e., riots—can be identified in Sub-Saharan Africa. To do so, we rely on monthly data at the cell level (0.5×0.5 degrees). Our baseline regression relates the level of rioting in a given cell and month to a proxy of the monthly deviation of the actual water balance from the normal one. This disaggregated approach is tailored to the frequent and localized nature of the phenomenon. Unlike conflicts between organized groups, which are usually measured as binary responses at higher levels of aggregation, riots flare up immediately in response to a stimulus, are short-lived, occur multiple times in a year, and are usually confined to the region affected by the stimulus. Although we do run regressions on the full sample, our preferred estimates will be based on a subsample of more populous cells (see Section 3). The reason is that

[10] Esteban et al. (2012) argue that in cases where the prize to be won is private (e.g., better access to water), ethnic divisions help restrict the benefits to smaller groups—and hence facilitate mobilization.

a basic requirement for riots to emerge, namely the presence of a substantial number of individuals with coordinated beliefs, is hardly met in cells that are sparsely populated.

To uncover any possible effect of the actual water balance on the level of rioting, we use the Standardized Precipitation-Evapotranspiration Index (SPEI) constructed by Vicente-Serrano et al. (2010). SPEI is a drought index that reflects a cell's climatic water balance (see again Section 3). An index value greater (less) than zero indicates an above-normal (below-normal) water balance. Apart from time-invariant factors such as latitude, SPEI is constructed from weather information only. It is therefore plausible to assume that SPEI is exogenous, i.e., that fluctuations in weather conditions are independent of any other potentially confounding factor. Nevertheless, we do control for other factors that possibly influence the level of rioting by using a rich set of fixed effects. In particular, we include cell fixed-effects to control for time-invariant cell characteristics that may affect rioting and water. We also rely on region-by-month fixed effects to control for region-specific seasonal patterns in the data. Specifically, the region-by-month fixed effects account for the possibility that—over our observation period of 22 years—the deviation of SPEI from its long-run average and the prevalence of rioting show systematic monthly patterns. Finally, we include country-by-year fixed effects to account as much as possible for time-varying factors at the country-level, such as significant changes to national policies (which usually do not occur at a frequency higher than yearly). In essence, by including a uniquely rich set of fixed effects, we explain a large share of the variation in riots. As a result, we argue that our estimates for SPEI identify the causal effect of SPEI on riots, i.e., that they are not biased by any unobserved third factor.

To sum up, our baseline regression equation to be estimated in Section 4 is given by

$$R^*_{it} = \alpha + \beta SPEI_{it} + \gamma_i + \delta_{rm} + \rho_{cy} + \varepsilon_{it}, \tag{1}$$

with i and t standing for cell and month, respectively. R^*_{it} is a measure of the level of rioting; γ_i refers to cell (i) fixed effects, while δ_{rm} and ρ_{cy} denote, respectively, the region-by-month (r and m) and the country-by-year (c and y) fixed effects (with the regions being Eastern, Western, Southern, and Middle Africa). The parameter of interest in equation

(1) is β, which is expected to have a negative sign.

In addition to equation (1), we estimate specifications that include interaction terms. The prime objective is to shed light on the mechanism linking riots to deviations (captured by SPEI) of the actual water balance from its normal level. Among others, we estimate specifications that include an interaction term involving SPEI and a measure of the supply of blue water in a cell;[11] specifications that include a triple interaction involving SPEI, the supply of blue water, and the prevalence of cropland in a cell; and specifications that include a triple interaction involving SPEI, the supply of blue water, and ethnic diversity. By including these interaction terms, we want to explore whether a possible effect of SPEI on riots may work through the "competition-for-water" channel. If this were the case, the signs of the coefficients should be negative: Following the logic of diminishing returns, the actual climatic water balance (i.e., precipitation less potential evapotranspiration) should matter more for the current production—and hence the competition-induced level of rioting—in cells that are characterized by a low supply of blue water (i.e., in cells which have only little surface and ground water). However, the actual water balance should be expected to matter even more if the supply of blue water is relatively low and the agricultural sector is relatively important (because water serves as a major input into agricultural production); similarly, the actual water balance should be expected to have a particularly strong effect if the the supply of blue water is relatively low and and the cell is ethnically diverse (because ethnic divisions may facilitate the mobilization of groups that participate in a riot). Finally, we consider a number of further possible interaction effects. For instance, we explore whether the effect of SPEI is stronger in months that are part of the growing season or in cells that are closer to urban centers.

Given the structure and the size of the raw dataset (long panel with more than 2,000,000 observations), we employ linear panel estimation throughout. That is, we follow the recent conflict literature (e.g., Harrari and La Ferrara, 2014; Hodler and Raschky 2014) in relying on a linear probability model when using a binary dependent variable.[12]

[11] This is essentially a time-invariant estimate of the total quantity of fresh surface and ground water that is available to catchment before any uses are satisfied (see again Section 3).

[12] The present dataset leaves us with two particular challenges that make the nonlinear estimation of the parameters of interest problematic. *First*, due to the highly disaggregated nature of our data, riots

3 Data

3.1 Data Sources and Descriptive Statistics

Our empirical analysis relies on several data sources. The information used to construct our dependent variables stems from the Social Conflict in Africa Database (SCAD). SCAD lists different types of social unrest (like strikes, demonstrations, or riots) starting from 1990 for all African countries with a population size of more than one million. The database was compiled by Salehyan et al. (2012) and is based on newswires from Associated Press and Agence France Presse. The data are geo-coded and contain detailed information on, among other things, event type and duration. SCAD does not include, however, violent events that are directly related to armed internal conflicts. Such events are covered by the PRIO/Uppsala ACLED dataset, i.e., by the data source that is typically used in the related conflict literature. The type of violent clashes we consider here are riots. SCAD defines a riot to be a "distinct, continuous, and violent action toward members of a distinct 'other' group or government authorities". We construct three different dependent variables at the cell-month level. The first two variables, NoD and Inc, are measures of the level of rioting. NoD is a count variable that gives the number of days with riots. Inc reflects riot incidence; it is a binary variable that equals one if we observe at least one riot. The third dependent variable, Ons, reflects riot onset; it is a binary variable that equals one if we observe at least one riot in t, but none in $t-1$. The two binary dependent variables are often used in the related conflict literature.

The main explanatory variable is the Standardized Precipitation-Evapotranspiration Index (SPEI), which was developed by Vicente-Serrano et al. (2010). SPEI is a drought index that reflects the climatic water balance at different time scales.[13] We consider

happen to be relatively rare events (relatively rare in terms of the numbers of cells and time periods we observe). King and Zeng (2001) show that this may lead to biased results when using non-linear estimation. *Second*, we are dealing with a long panel ($T = 264$) and use a large number of cross-sectional and time fixed-effects. In a recent paper, Fernandez-Val and Weidner (2014) show that this can cause biased results in a nonlinear setting.

[13] There are alternatives to SPEI, in particular PDSI, which is used by Couttenier and Soubeyran (2014). We chose to use SPEI because of its higher level of disaggregation. Given that we consider riots, the high level of spatial and temporal disaggregation is an important part of our empirical strategy.

the monthly climatic water balance, i.e., the monthly difference between precipitation and potential evapotranspiration (using SPEIbase V2.2). SPEI is a standardized variable that expresses the water balance in units of standard deviations from the long-run average (which is calculated over the 1901-2012 period). A value of zero means that the water balance is exactly at its long-run average; a value of plus one (minus one) means that the water balance is one standard deviation above (below) the long-run average, etc.

The climatic water balance is an important factor affecting vegetation activity. According to Vicente-Serrano et al. (2012), the correlation between the water balance and vegetation activity is particularly strong and immediate under arid, semi-arid, and subhumid conditions, i.e., under conditions present in many parts of Africa's agricultural regions. Moreover, in many African countries, production at the farm level is highly diversified in terms of crops (see, e.g., Chavas and Di Falco, 2012), implying that the growing and harvest season tends to cover a large part of the year. This, together with the strong correlation between SPEI and vegetation activity, suggests that the actual water balance matters for agricultural productivity throughout the year. The same holds for other types of water-dependent economic activities, like pastoralism. So unusual dryness can be expected to increase competition for water roughly all the year round.[14]

In addition to SCAD and the SPEI database, we work with a variety of other data sources. Most importantly, we rely on data provided by Gassert et al. (2014) and Ramankutty et al. (2008) to explore whether the impact of SPEI on riots possibly works through the competition-for-water mechanism, as described in Section 2. Ramankutty et al. (2008) is the source of the data on the share of cropland in each cell. Gassert and coauthors provide estimates of the total supply of blue water (i.e., fresh surface and ground water) that is available to a catchment (in our case, a cell) before any uses are satisfied. More precisely, blue water (in m^3) is calculated as all water flowing into a catchment from upstream catchments (net of estimated upstream consumption) plus any imports of water to the catchment. Essentially, blue water includes rivers, lakes, and underground water, i.e., water sources that—particularly under unusually dry weather conditions—become

[14] We do explore, however, whether the impact of SPEI on riots is stronger in the main growing season.

important for irrigation, the watering of animals, and other productive uses.

We further rely on population data (Tollefsen et al., 2012; "PRIO-GRID") as we restrict our empirical analysis to areas with a certain population size. From the same source, we make use of a number of other cell-level variables to explore additional possible interaction effects. These variables are: The number of distinct ethnic groups in a cell; the share of arable land equipped for irrigation within each cell; the estimated cell-average travel time (in minutes) by land transportation from the cell to the nearest major city; and, for some robustness checks, the distance to the national capital.

To account for the main growing season in a cell, which we do in some of the estimates, we use growing seasons surfaces derived specifically for Sub-Saharan Africa by HarvestChoice (2010). HarvestChoice uses actual reflectance values combined with greening up/down data derived from MODIS satellite images. These data are available for four years (2001-2004) and provide a comprehensive picture of the start and end days of the growing season for each year based on the Enhanced Vegetation Index (EVI). The EVI is a refined vegetation index that "de-couples" the canopy background signal and reduces atmospheric influences. The data sets were aggregated at the 10×10 km resolution and analyzed together to determine the start and end dates for each calendar year and whether the pixel represents a bimodal area (i.e., an area with two or more distinct growing seasons). The annual values were then compared to determine a representation of the start and end dates of the growing season for a given pixel.[15] We use this pixel-level information on start and end dates to determine the "average growing season" at the cell level (0.5×0.5 degree).[16] This, in turn, allows us to compute a monthly dummy equal to one if a given month is part of the average growing season in a cell.

Finally, we rely on the relevant United Nations Statistics Division classification to assign each 0.5×0.5 degree cell to a Sub-Saharan region (Eastern, Western, Southern,

[15] A detailed description of how these data were used to determine the start, end, length, and modality of the growing season is available directly on the HarvestChoice website (http://harvestchoice.org/labs/measuring-growing-seasons).

[16] We also experimented with two alternative definitions of the growing season. One was based on median start and end dates. The other alternative was defined by the start and end dates of the main crop. The exact definition of the growing season does not matter for the results in Section 4.

Table 1: Summary statistics

Variable	(1) Mean	(2) Std. Dev.	(3) Min.	(4) Max.	(5) N
NoD	0.002046	0.15998	0	31	2006120
Inc	0.000753	0.027434	0	1	2006120
Ons	0.000655	0.025594	0	1	2006120
SPEI	-0.163	0.996	-8.506	6.68	1910722
Water	3017155.77	23618873.44	0	1159684096	1998667
Crop	0.083	0.138	0	1	1977080
Pop	76696.532	190084.118	0	5399045.5	2001571
Irrigation	0.959552	2.544508	0	32.868999	1091484
Travel Time	704.207773	751.274564	0	6133	2001632
Ethn Groups	1.756197	1.076215	1	7	1433466
Cap Dist	601.483731	398.630259	4	1941	2001632
Grow Season	0.350485	0.477122	0	1	2006120

Note: Summary statistics for the full sample. NoD: number of days with riots; Inc: binary indicator that equals one if at least one riot is observed; Ons: binary indicator that equals one if at least one riot is observed in t, but none in t - 1; SPEI: Standardized Precipitation-Evapotranspiration Index; Water: available water per capita (in m^3/pop); Crop: share of land used for growing crops or pasture; Pop: population size; Irrigation: irrigated area as share of cell area (in %); Travel Time: travel time to nearest urban center (cell average, in minutes); Ethn Groups: number of ethnic groups in cell; Cap Dist: distance to national capital (in km); Grow Season: dummy variable indicating whether month can be classified as part of the growing season.

and Middle Africa), which allows us to construct the region-by-month fixed effects. Table 1 provides summary statistics for the variables used in our empirical analysis.

3.2 Geographical Characteristics of Rioting

Many regions in Sub-Saharan Africa are characterized by types of land that are hostile to human settlement (e.g., deserts, regularly flooded areas, or dense forests). These regions typically show a low populations density, implying that—as discussed in Section 2—they will hardly experience any riots. For this reason, we group cells according to the population distribution for each country (i.e., we compute the different deciles for each country separately) and focus on cells in which the population is greater than the population at a specific decile of the relevant country's distribution. Table 2 shows descriptive statistics for cells which are, respectively, above the 1st, the 2nd, $\cdots$, and the 9th decile.

Column 3 of the table shows that more than 82 percent of all observations with at least one riot are covered by cells with a population greater than the population at the 6th

Table 2: Descriptive Statistics based on population deciles

(1) Decile	(2) N (cells)	(3) Rioting	(4) SPEI	(5) Cropland	(6) Population
1	6,810	.971542	-.15655722	.08757274	11221
2	6,062	.9569821	-.1516641	.09185871	16194
3	5,294	.943084	-.1424928	.09699274	21706
4	4,549	.9285241	-.13848273	.10282339	28095
5	3,802	.8762409	-.13378653	.1098709	37054
6	3,034	.8232958	-.12856168	.11767683	51319
7	2,278	.7372601	-.12379031	.12722936	72006
8	1,518	.6512243	-.1154652	.1386438	105547
9	756	.5201853	-.10765097	.15088922	172342

Note: The different rows show summary statistics for various variables when restricting the sample to cells with a population greater than the population at certain deciles (listed in Column 1) of the relevant country's distribution. Column 2 indicates the number of observations that are left when focusing on cells with a population above a specific decile. Column 3 shows the share of observations with at least one riot that are covered by the restricted sample. Column 4 indicates the average SPEI for the restricted sample. Column 5 contains the average percentage of cropland in the restricted sample and Column 6 shows the average population of the cells that are at the respective decile.

decile of the relevant country's distribution. When we take the 9th decile as the threshold, the corresponding number is still 52 percent. It can also be seen that the average share of cropland increases with the size of the population. While only an average of around 9 percent of the overall cell area is cropland when we exclude cells in the 1st decile, more than 15 percent on average is used for growing crops when we focus on cells above 9th decile. Evidently, being restrictive in terms of population size comes at the cost of losing a substantial share of cells and—to a lesser extent—also of losing incidences of rioting. In the following empirical analysis, we therefore focus on cells with a population greater than the population at the 6th decile of the relevant country's distribution. In doing so, we still cover more than 82 percent of all observations with at least one riot. Imposing this restriction implies that the share of observations with at least one riot rises from 0.08 to 0.16 percent, while the share of cells with at least one riot (over the entire period) rises from 6.7 to 12.3 percent. At the same time, the average share of land used for growing crops increases from less than 9 percent to about 12 percent. Note, however, that we also report results that are based on different population restrictions, including the results we obtain when using the full sample.

4 Results

4.1 Main Results

Table 3 shows the results for the baseline specification when we restrict our sample to cells with a population above the 6th decile (evaluated at the country level). The differences in the estimates between the alternative specifications (Columns 1–3, 4–6, and 7–9) stem from the use of different sets of fixed effects, as indicated by the lower half of Table 3. As described in Section 2, γ_i, δ_{rm}, and ρ_{cy} stand for cell, region-by-month, and country-by-year fixed effects, respectively (see also the notes at the bottom of the table). Table 8 in the Appendix displays results based on alternative population restrictions. These additional results will be briefly discussed in the following subsection.

The signs of the parameter estimates for SPEI shown in Table 3 are negative throughout, as expected. In particular, there is a significant negative relationship between SPEI and the level of rioting: When we use Inc, the binary measure, as a proxy for the level of rioting, the relationship is highly significant; when we rely on NoD, the count measure, the relationship is at least marginally significant (note that the vast majority of rioting incidences in our dataset— 91%—only last for a week or less). We further observe that a drop in SPEI has a highly significant impact on the onset of riots.

In terms of magnitude, the estimation results in Table 3 suggest that a one-standard-deviation decrease in SPEI (signaling drier conditions) increases the probability of observing a riot in a given cell and month by 8.5 percent for the average cell in our restricted sample.[17] Similarly, a one-standard-deviation decrease in SPEI translates in an increase in the number of days with riots in a given cell and month of 9 percent. This implies a rather substantial effect when calculated at the yearly level—assuming that the change in SPEI would be constant throughout the year and for all cells.

Having identified an effect of the actual water balance on the current level of rioting,

[17] A one standard deviation below the mean in the SPEI increases the likelihood to observe a riot in a cell in a month by 0.0132 percentage points. The unconditional probability of having a riot in a cell (with population above the 6th decile) in a month is 0.0016. A drop of one standard deviation in the SPEI thus increases the likelihood of having a riot on the average cell by around 8.5%.

Table 3: Baseline specifications

	(1) NoD	(2) Inc	(3) Ons	(4) NoD	(5) Inc	(6) Ons	(7) NoD	(8) Inc	(9) Ons
SPEI	-0.000358	-0.000132	-0.000134	-0.000361	-0.000130	-0.000133	-0.000367	-0.000131	-0.000133
	(0.135)	(0.009)	(0.003)	(0.130)	(0.010)	(0.004)	(0.090)	(0.007)	(0.004)
N	773384	773384	773384	773384	773384	773384	773384	773384	773384
NoG	2939	2939	2939	2939	2939	2939	2939	2939	2939
T_{min}	25	25	25	25	25	25	25	25	25
T_{mean}	263.1	263.1	263.1	263.1	263.1	263.1	263.1	263.1	263.1
T_{max}	264	264	264	264	264	264	264	264	264
γ_i	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
δ_{rm}	Yes	Yes	Yes				Yes	Yes	Yes
ρ_{cy}	Yes	Yes	Yes	Yes	Yes	Yes			
δ_m				Yes	Yes	Yes			
ρ_y							Yes	Yes	Yes

Note: p-values in parentheses. Standard errors are clustered at the cell level. NoD: number of days with riots; Inc: binary indicator that equals one if at least one riot is observed; Ons: binary indicator that equals one if at least one riot is observed in t, but none in t - 1; N: number of observations; NoG: number of cells; T_{min}, T_{mean}, and T_{max}: minimum, mean, and maximum number of months available for all cells in the sample. γ_i: cell fixed effects; δ_{rm}: region-by-month fixed effects; ρ_{cy}: country-by-year fixed effects; δ_m: month fixed effects; ρ_y: year fixed effects.

we are now interested in a possible mechanism linking the two variables. If unusually dry weather conditions affect the level of rioting by intensifying the competition for water, as hypothesized in Section 2, we suspect the impact of SPEI on riots to be stronger in cells with a relatively low supply of blue water and a relatively important agricultural sector (which is a major consumer of water). Table 4 presents several specifications testing for the presence of such interaction effects. Columns 1–9 of Panel A show results when we include a simple interaction term SPEI×Water(xth), where Water(xth) is a dummy variable that equals one if the supply of blue water (in per-capita terms) is below the xth percentile of our restricted sample, where $x \in \{50, 25, 10\}$. We observe that blue water scarcity significantly increases the effect of SPEI on riots, with the size of the increase rising in water scarcity. For instance, the estimated marginal effect of SPEI on Inc in cells below the 25th percentile (Table 4, Panel A, Column 5) is more than three times larger than the corresponding baseline estimate presented in Table 3, Column 2.

Panel B of Table 4 addresses the question whether the effect of SPEI is even stronger in cells characterized by a combination of blue water scarcity and substantial agricultural activity. This is in fact the case. The results in Columns 1–9 are based on specifications that include triple interactions of the form SPEI$\times$Water(10th)$\times$Crop(xth), where Crop(xth) is a dummy variable that equals one if the share of cropland in a cell is above the xth percentile of our restricted sample, where $x \in \{10, 25, 50\}$. We observe that—relative to the baseline specifications in Table 3—the effect of SPEI is larger in cells that combine a low supply of blue water with a relatively substantial share of cropland; moreover, the increase in the impact of SPEI rises when we apply a stricter definition regarding what is meant by a "relatively substantial" share of cropland.[18] Finally, a comparison of Panels A and B shows that—relative to cells with blue water scarcity but no particular importance of cropland—the effect of SPEI is larger in cells that are characterized by both water scarcity and a relatively substantial share of cropland.

We complete our analysis by testing whether ethnic diversity leads to a quantitatively stronger relationship between unusual dryness and riots. Table 5, Panel A, shows the results from estimating the baseline specification supplemented with a simple interaction term SPEI$\times$ED, where ED is a dummy variable that equals one if there is more than one ethnic group in a cell. We observe that, in fact, the effect of SPEI on riots is larger in cells with more than one ethnic group (it is also interesting to see that the overall effect of SPEI becomes insignificant). Panel B of the table presents results based on specifications that include triple interactions of the form SPEI$\times$Water(xth)$\times$ED, where $x \in \{50, 25, 10\}$. Apparently, in cells with a comparatively low supply of blue water, ethnic diversity has an even larger impact on the size of the marginal effect of SPEI. Column 2 of Panel A suggests that ethnic diversity raises the marginal effect of SPEI on riot incidence by a factor 3.5. However, according to Panel B, ethnic diversity matters generally more in cells with a low supply of blue water. For instance, if we define the threshold in this regard to be the 25th percentile (Column 5), ethnic diversity raises the marginal effect of SPEI by a factor 7.2 in cells with a low supply of blue water.

[18]Note that we also find negative and significant effects (for Inc and Ons) when we include simple interaction terms of the form SPEI$\times$Crop(xth).

Table 4: Interaction effects: Water scarcity and share of cropland

Panel A	(1) NoD	(2) Inc	(3) Ons	(4) NoD	(5) Inc	(6) Ons	(7) NoD	(8) Inc	(9) Ons
SPEI	-0.000122	-0.0000437	-0.0000602	-0.0000763	-0.0000453	-0.0000577	-0.0000698	-0.0000635	-0.0000790
	(0.594)	(0.277)	(0.122)	(0.712)	(0.243)	(0.114)	(0.726)	(0.104)	(0.034)
. ×Water(50th)	-0.000493	-0.000184	-0.000155						
	(0.295)	(0.070)	(0.100)						
. ×Water(25th)				-0.00125	-0.000385	-0.000341			
				(0.181)	(0.026)	(0.036)			
. ×Water(10th)							-0.00350	-0.000833	-0.000672
							(0.138)	(0.035)	(0.067)
N	773384	773384	773384	773384	773384	773384	773384	773384	773384

Panel B	(1) NoD	(2) Inc	(3) Ons	(4) NoD	(5) Inc	(6) Ons	(7) NoD	(8) Inc	(9) Ons
SPEI	-0.0000667	-0.0000662	-0.0000834	-0.0000683	-0.0000675	-0.0000845	-0.0000564	-0.0000720	-0.0000912
	(0.735)	(0.087)	(0.024)	(0.727)	(0.079)	(0.022)	(0.775)	(0.060)	(0.013)
. ×Water(10th) & ×Crop(10th)	-0.00402	-0.000909	-0.000703						
	(0.131)	(0.041)	(0.088)						
. ×Water(10th) & ×Crop(25th)				-0.00439	-0.000977	-0.000754			
				(0.132)	(0.045)	(0.094)			
. ×Water(10th) & ×Crop(50th)							-0.00573	-0.00114	-0.000820
							(0.112)	(0.059)	(0.142)
N	773384	773384	773384	773384	773384	773384	773384	773384	773384

Note: p-values in parentheses. All specifications include cell (γ_i), region-by-month (δ_{rm}), and country-by-year (ρ_{cy}) fixed effects. Panel A: Water (50th, 25th, and 10th) are dummy variables for cells with a below median, 25th, and 10th percentile (restricted sample) water availability per capita, respectively. Panel B: See above for the definition of Water. Crop(10th, 25th, and 50th) are dummy variables for cells with a share of cropland above the 10th, 25th, and 50th percentile (restricted sample), respectively.

Table 5: Interaction effects: Water scarcity and ethnic diversity

Panel A	(1) NoD	(2) Inc	(3) Ons
SPEI	0.0000170	-0.0000694	-0.0000674
	(0.940)	(0.191)	(0.163)
. ×ED	-0.00105	-0.000175	-0.000187
	(0.067)	(0.113)	(0.069)
N	773384	773384	773384

Panel B	(1) NoD	(2) Inc	(3) Ons	(4) NoD	(5) Inc	(6) Ons	(7) NoD	(8) Inc	(9) Ons
SPEI	-0.0000461	-0.0000747	-0.0000769	-0.0000860	-0.0000819	-0.0000861	-0.000113	-0.000103	-0.000109
	(0.803)	(0.099)	(0.062)	(0.654)	(0.057)	(0.028)	(0.565)	(0.018)	(0.007)
. ×Water(50th)×ED	-0.00162	-0.000297	-0.000298						
	(0.093)	(0.092)	(0.063)						
. ×Water(25th)×ED				-0.00278	-0.000511	-0.000492			
				(0.163)	(0.083)	(0.072)			
. ×Water(10th)×ED							-0.00621	-0.000725	-0.000640
							(0.184)	(0.241)	(0.269)
N	773384	773384	773384	773384	773384	773384	773384	773384	773384

Note: p-values in parentheses. All specifications include cell (γ_i), region-by-month (δ_{rm}), and country-by-year (ρ_{cy}) fixed effects. Water (50th, 25th, and 10th) are dummy variables for cells with a below median, 25th, and 10th percentile (restricted sample) water availability per capita, respectively. ED is a dummy variable that equals one if there is more than one ethnic group in a cell.

In sum, we consistently find that unusually dry weather conditions have a stronger effect on the level of rioting when blue water is relatively scarce; the impact of SPEI is even stronger when blue water scarcity is combined with a relatively strong agricultural sector (i.e., when water is a particularly important input factor) or with ethnic diversity (i.e., when mobilizing participants for a conflict is relatively easy). These findings are supportive of the widely held belief that unusual dryness influence the level of low-scale violence through a competition-for-water mechanism.

4.2 Further Interactions

Besides blue water scarcity, the prevalence of cropland, and ethnic diversity, there may be other factors influencing to what extent the climatic water balance affects the probability of riots. It is the purpose of this subsection to empirically explore a number of such alternative factors. Following Harari and La Ferrara (2014), we start by looking at the interaction between SPEI and a dummy variable "Growing Season" (which indicates whether a particular month is part of the cell's average growing season). The conjecture is that actual water balance may have a stronger effect on agricultural yields—and hence the competition for water—within the average growing season than during the rest of the year. This is, however, not the case in our data: The interaction SPEI×Growing Season is insignificant (while SPEI remains significant), as can be seen from Columns 1–3 of Table 6. The lack of a significant interaction is probably less of a surprise when we consider that—as discussed in Section 3—agricultural production at the farm level tends to be highly diversified in terms of crops (Chavas and Di Falco, 2012).

Diversification can also be observed at a higher level. Our data show that in many cells the main crop varies substantially across the different sub-regions of a cell: We find that more than 60% of the cells in our sample include sub-regions which differ in the start date of their growing seasons by more than 10 weeks.[19] Moreover, neither pastoral water conflicts nor conflicts over access to blue water for industrial production or household

[19] The average standard deviation of the starting week of the growing season within a cell is 7 weeks (the growing season starts on average in week 16); the average standard deviation of the length of the growing season within a cell is 9 weeks (the length of the growing season is on average 19 weeks).

Table 6: Interaction effects: Growing season

	(1) NoD	(2) Inc	(3) Ons	(4) Inc	(5) Inc
SPEI	-0.000562	-0.000133	-0.000134	-0.000144	-0.000228
	(0.036)	(0.035)	(0.017)	(0.958)	(0.857)
. ×Growing Season	0.000554	0.00000311	-0.00000119		
	(0.120)	(0.973)	(0.989)		
N	773384	773384	773384	55966	127519

Note: p-values in parentheses. All specifications include cell (γ_i), region-by-month (δ_{rm}), and country-by-year (ρ_{cy}) fixed effects. Columns 1–3 display the results for our baseline specification introducing an interaction effect (dummy for growing season x SPEI). Columns 4 and 5 show results for yearly data, i.e. when aggregating our monthly data at the yearly level. Following Harari and La Ferrara (2014), we aggregated the SPEI index by only considering shocks during the growing season. More specifically, we count the number of growing season months in a year for which the SPEI is smaller than -1. Finally, we calculate the share of growing season months for which the SPEI is below this threshold.

consumption are likely to be confined to the growing season.

We are also left with insignificant results when we aggregate our data on a yearly level and use a specification that is similar to Harrari and La Ferrara (2014). The results are shown in Column 4 (restricted sample) and Column 5 (full sample) of Table 6. We suspect that this difference between riots and civil conflicts stems from the fact that the two forms of conflict are very different in nature, triggered by different mechanisms.

Table 7 reports results for specifications that include further plausible interactions, namely: The interaction between SPEI and the dummy variable "Irrigation" (equal to one if the proportion of arable land in a cell equipped for irrigation is above the mean of our sample) and the interaction between SPEI and the dummy variable "Urban Area" (equal to one if the average travel time to the closest urban centre is less than 2 hours).

The numbers in Columns 1–3 of Table 7 do not suggest that a comparatively high prevalence of irrigation systems would mitigate the impact of SPEI. A possible explanation is that even among the cells with a comparatively high reliance on irrigation systems the share of irrigated land is on average only 5.1%, reflecting that the prevalence of irrigation in Sub-Saharan Africa is the lowest of any region in the world (Burney et al., 2013). Finally, Columns 4–6 of Table 7 suggest that SPEI has a stronger effect on rioting in cells

Table 7: Interaction effects: Irrigation and distance from an urban center

	(1) NoD	(2) Inc	(3) Ons	(4) NoD	(5) Inc	(6) Ons
SPEI	-0.000349	-0.0000980	-0.0000867	-0.0000557	-0.0000622	-0.0000702
	(0.276)	(0.256)	(0.262)	(0.768)	(0.092)	(0.048)
. ×Irrigation	-0.00120	-0.000114	-0.0000596			
	(0.380)	(0.585)	(0.744)			
. ×Urban Area				-0.00634	-0.00146	-0.00134
				(0.096)	(0.033)	(0.031)
N	421741	421741	421741	773384	773384	773384

Note: p-values in parentheses. All specifications include cell (γ_i), region-by-month (δ_{rm}), and country-by-year (ρ_{cy}) fixed effects. The irrigation dummy is equal to one if the underlying variable is larger than the mean of the restricted sample. The urban-area dummy is equal to one if the average travel time to the nearest urban center is less than two hours.

where the average travel time to the closest urban area is relatively short. This result is consistent with the view that urban areas create a higher pressure on water resources (thereby enhancing the competition for water) and provide fertile ground for riots as they facilitate the formation of crowds.

4.3 Robustness

Tables 9 to 12 in the Appendix report the results of several robustness checks, including different sample restrictions (from the full sample to the 9th decile of population).

Table 9 shows results when we control for the potential persistence of the dependent variable,[20] for lags and leads of SPEI, and for an interaction of SPEI with its first lag. According to Columns 1–3 and 7–9, the inclusion of various lags of the dependent variable does not change the estimated impact of SPEI by much (in absolute terms, the point estimates turn slightly bigger). However, one difference worth noticing concerns the statistical significance of the estimates relying on NoD, our count measure, as the dependent variable. While the estimated impact of SPEI on NoD is only marginally significant in Table 3, it is highly significant when we introduce lagged values of NoD. Note further that

[20] Given the long time dimension of our dataset (263 months on average) we employ standard fixed-effects regression as the Nickell (1981) bias is negligible in our case.

the inclusion of lags (Columns 3–6) and leads (Columns 10–12) of SPEI does not substantially affect the estimated contemporaneous impact of SPEI either. As for the lags and leads themselves, the estimates are rather small and no clear picture emerges. This is not surprising as some factors used to calculate SPEI are time-invariant. The same applies when including SPEI and the interaction between SPEI and its first lag. The estimates for the contemporaneous SPEI are comparable to previous specifications in terms of size and remain statistically significant. The interaction term, however, is insignificant.

Table 8 returns to the baseline specification and reports findings for alternative sample restrictions. Being more restrictive in terms of population leads to higher parameter estimates (in absolute terms), indicating a stronger effect of SPEI in more populous cells. For instance, when we include all cells above the 5th decile, a one-standard-deviation decrease in SPEI rises the likelihood of observing at least one riot by 7.3 percent; when only cells above the 9th decile are included, the corresponding number is 25.2 percent.

The baseline results are again confirmed when we estimate a standard first-differenced (fd) specification, as shown in Columns 1–3 of Table 10. The fd-estimates are just slightly more significant, both in economic and statistical terms. Moreover, when we relate the level of rioting, or riot onset, to changes in SPEI (i.e., $SPEI_t - SPEI_{t-1}$), we also tend to find a significant negative relationship (see Columns 4–6 of Table 10).

Table 11 reports results for different types of standard errors. So far, all standard errors have been clustered at the cell level. However, given the precision of our data in terms of both space and time, different forms of spatial dependence and autocorrelation may affect standard errors. Columns 1–3 of Table 11 therefore report results based on standard errors that are robust to spatial and temporal dependence (Driscoll and Kraay, 1998) and Columns 4–6 display results for classical heteroscedasticity and autocorrelation consistent (HAC) standard errors (Newey and West, 1994). The table suggests that our baseline results are highly robust to changes in the type of standard errors used.

Finally, Table 12 reports results based on non-linear specifications, namely Negative Binomial and Logit. These estimations are consistent with the results in the previous tables: Unusually dry weather conditions tends to increase the level of rioting. As expected, the effect is stronger in quantitative terms when using non-linear specifications (allowing to control for the high number of zeros in the dependent variable). However, nonlinear specifications come at a cost, as discussed at the end of Section 2.

5 Conclusion

Violent and spontaneous clashes between different groups—riots—are a widespread phenomenon in poorer places. It is undisputed that frequent outbursts of riots are an obstacle to economic development as they disrupt commerce and basic government functions. Our data from Sub-Saharan Africa suggest that riots are also costly in terms of human lives. Over the 1990–2012 period, the average riot was associated with 66 fatalities.

Even though riots pose a serious problem in Africa and beyond, the internal-conflict literature has so far mostly focused on explaining conflict between organized groups, such as coups, rebellions, or revolutions. This paper, by contrast, explores a possible trigger of riots. In particular, it empirically investigates how unusually dry weather conditions affect the level of rioting in a certain area. Anecdotal evidence suggests that unusual dryness provokes riots by intensifying the competition over access to scarce water resources.

Our empirical strategy is precisely tailored to the phenomenon we study. Unlike civil conflicts, riots are short-lived and local events. We accommodate these specifics by relying on highly disaggregated data (monthly, at the 0.5×0.5-degree cell level). Our proxy for weather anomalies is the SPEI drought index, which indicates the deviation of the actual climatic water balance in a given cell and month form the balance that prevail on average at this location and time. Moreover, we rely on a rich set of fixed effects, a strategy that makes it highly plausible that any effect of SPEI on the level of rioting we detect is in fact causal. We find that a one-standard-deviation decrease in SPEI rises the likelihood of a riot in a given cell and month by 8.5 percent. Additional estimations support the view that the actual water balance influences the level of rioting through the competition-for-water mechanism. In particular, we find that unusually dry (wet) conditions have a stronger postive (negative) impact on the level of rioting in cells that have a low supply of blue water—and an even stronger impact in cells that combine a low supply of blue water with a high demand for water (coming from agriculture).

Our empirical findings have important policy implications. They suggest that, particularly in Sub-Saharan regions that combine a scarcity of blue water with significant agricultural activity, measures that improve the efficiency of agricultural water usage yield gains that go beyond the immediate impact on agricultural production and food security. By lowering the demand for irrigation water, such measures can be expected to dampen the effect of unusually dry weather conditions on the ferocity of the competition for access to water resources; as a result, improvements in the efficiency of water usage may lead to the additional gain of reducing the risk of violent clashes during droughts.

By exploring a specific trigger of riots, the present paper gives also rise to a number of new questions that will be interesting to address. For instance, anecdotal evidence suggests that "big" events like rebellions or revolutions are often preceded by periods with high levels of rioting (while, of course, not all periods with high levels of rioting are followed by rebellions or revolutions). So an obvious question would be whether we find such correlations in the data. Similarly, it would be important to have a model that would allow us to explore the circumstances under which a series of riots is more likely to escalate into a full-blown rebellion or revolution. Addressing these questions would help to fill the void between research on rioting and the literature on conflict between organized groups. At the moment, we leave these questions to future research.

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Appendix

Table 8: Estimation results for different sample restrictions

	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	Ons
spei	-0.000134	-0.0000397	-0.0000448	-0.000126	-0.0000474	-0.0000511	-0.000136	-0.0000537	-0.0000582
	(0.293)	(0.078)	(0.028)	(0.347)	(0.052)	(0.021)	(0.369)	(0.048)	(0.019)
N	1910722	1910722	1910722	1739426	1739426	1739426	1550930	1550930	1550930
Decile	Full	Full	Full	1	1	1	2	2	2

	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	Ons
spei	-0.000156	-0.0000641	-0.0000692	-0.000158	-0.0000735	-0.0000796	-0.000263	-0.0000968	-0.000103
	(0.378)	(0.039)	(0.014)	(0.454)	(0.040)	(0.014)	(0.174)	(0.019)	(0.006)
N	1353328	1353328	1353328	1163414	1163414	1163414	971081	971081	971081
Decile	3	3	3	4	4	4	5	5	5

	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	Ons
spei	-0.000430	-0.000168	-0.000173	-0.000537	-0.000247	-0.000245	-0.000997	-0.000480	-0.000437
	(0.105)	(0.009)	(0.003)	(0.119)	(0.008)	(0.003)	(0.107)	(0.006)	(0.004)
N	580901	580901	580901	384091	384091	384091	186820	186820	186820
Decile	7	7	7	8	8	8	9	9	9

Note: p-values in parenthesis. Standard errors are clustered at the cell level. NoD: number of days with riots; Inc: binary indicator that equals one if at least one riot is observed; Ons: binary indicator that equals one if at least on riot is observed in t, but none in t - 1; N: number of observations; Decile: population threshold (referring to the country-level distribution) above which a cell is included in the sample. *Full* stands for the full sample without any restriction. All specifications include cell (γ_i), region-by-month (δ_{rm}), and country-by-year (ρ_{cy}) fixed effects.

Table 9: Estimation results including lags of the dependent variables and SPEI

	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	Ons
DV, L 1	0.398	0.0779	-0.0354				0.408	0.0818	-0.0355						
	(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)						
DV, L 2	0.0241	0.0227	0.00407												
	(0.493)	(0.006)	(0.494)												
DV, L 3	0.000857	0.0211	0.0120												
	(0.964)	(0.002)	(0.030)												
SPEI	-0.000497	-0.000147	-0.000143	-0.000383	-0.000150	-0.000152	-0.000469	-0.000135	-0.000136	-0.000385	-0.000138	-0.000141	-0 .000362	-0.000141	-0.000140
	(0.023)	(0.005)	(0.002)	(0.108)	(0.004)	(0.002)	(0.032)	(0.008)	(0.003)	(0.102)	(0.007)	(0.003)	(0.154)	(0.006)	(0.002)
., L 1				-0.0000181	0.0000870	0.0000903									
				(0.931)	(0.087)	(0.062)									
., L 2				-0.000323	-0.000104	-0.0000791									
				(0.255)	(0.012)	(0.055)									
., L 3				-0.000459	-0.0000318	-0.0000266									
				(0.035)	(0.451)	(0.518)									
., F 1										0.000197	0.00000781	-0.00000293			
										(0.259)	(0.867)	(0.947)			
., F 2										0.000541	0.0000917	0.0000844			
										(0.107)	(0.070)	(0.059)			
., F 3										0.000374	0.0000213	0.00000420			
										(0.244)	(0.624)	(0.921)			
. × L 1													-0 .00000117	-0.0000374	-0.0000204
													(0.995)	(0.306)	(0.554)
N	764457	764457	764457	761474	761474	761474	770408	770408	770408	761474	761474	761474	769406	769406	769406

Note: p-values in parentheses. Standard errors are clustered at the cell level. NoD: number of days with riots; Inc: binary indicator that equals one if at least one riot is observed; Ons: binary indicator that equals one if at least on riot is observed in t, but none in t - 1; N: number of observations. All specifications include cell (γ_i), region-by-month (δ_{rm}), and country-by-year (ρ_{cy}) fixed effects. DV, L 1-L 3 stand for lags 1-3 of the dependent variable (DV). '., L' and '., F' stand for, respectively, the lags and leads of SPEI, while '.× L 1' represents the interaction of SPEI with its first lag.

Table 10: Estimation results for first-differenced specifications

	NoD, fd	Inc, fd	Ons, fd	NoD	Inc	Ons
SPEI, fd	-0.000472	-0.000191	-0.000189	-0.000156	-0.000110	-0.000113
	(0.037)	(0.006)	(0.004)	(0.276)	(0.006)	(0.004)
N	769406	769406	769406	769406	769406	769406

Note: Columns 1–3 present results for the first-differenced specification excluding cell fixed effects (γ_i), but including region-by-month (δ_{rm}) and country-by-year (ρ_{cy}) fixed effects. Columns 4–6 display estimates for the baselines specification including the full set of fixed effects, but using the first difference of SPEI ($SPEI_{it} - SPEI_{it-1}$) instead of the level.

Table 11: Estimation results for different types of standard errors

	NoD	Inc	Ons	NoD	Inc	Ons
SPEI	-0.000364	-0.000126	-0.000129	-0.000364	-0.000126	-0.000129
	(0.111)	(0.030)	(0.020)	(0.150)	(0.003)	(0.001)
N	773384	773384	773384	773384	773384	773384

Note: p-values in parenthesis. All specifications include cell (γ_i), region-by-month (δ_{rm}), and year (ρ_y) fixed effects. Columns 1–3 report specifications using standard errors that are robust to spatial and temporal dependence (Discroll and Kraay, 1998). Columns 4–6 show results for heteroscedasticity and autocorrelation consistent (HAC) standard errors (Newey and West, 1994).

Table 12: Nonlinear specifications, negative binomial and logit

	NoD	Inc	Ons	NoD	Inc	Ons
spei	-0.0805	-0.0154	-0.0154	-0.0537	-0.0116	-0.0116
	(0.010)	(0.007)	(0.007)	(0.060)	(0.024)	(0.024)
N	93458	93458	93458	127266	127266	127266

Note: p-values in parentheses. All specifications include cell (γ_i), month (δ_m), and year (ρ_y) fixed effects. Columns 1 and 4 report results for the conditional fixed-effects negative binomial model with the number of days (NoD) with incidences of rioting as the dependent variable. Likewise, columns 2, 3, 5 and 6 contain results for the conditional fixed-effects logit with our indicator variables for riot incidences (Inc, columns 2 and 5) and onset (columns 3 and 6) as the dependent variables. Parameter estimates represent average marginal effects. The reduced sample size stems from the fact that rioting does not affect all cells and therefore cells without rioting are automatically omitted from the analysis.