Agricultural shocks and riots: a disaggregated analysis*

Christian Almer[†] Jérémy Laurent-Lucchetti[‡] Manuel Oechslin[§]

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Abstract

Every year, riots cause a substantial number of fatalities in less-advanced countries. This paper explores the role of agricultural shocks in explaining riots. Unlike civil wars, riots tend to die down quickly and are usually geographically confined. These particularities are reflected in our empirical strategy which relies on monthly data at the cell level (0.5×0.5 degrees). Using a drought index to proxy for agricultural output shocks, we find a negative relationship for Sub-Saharan Africa: A one-standard-deviation decrease in the drought index (signaling drier conditions) raises the likelihood of a riot in a given cell and month by 8.5 percent. Further investigations show that the effect is even larger in agricultural areas with limited water supply.

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[†]University of Bath, Department of Economics, Claverton Down, Bath BA2 7AY, United Kingdom; phone: +44 1225 38 6021; email: c.almer@bath.ac.uk.

[‡]University of Geneva, Department of Economics, Bd du Pont d'Arve 40, 1211 Genève, Switzerland; phone: +41 22 379 8281; email: jeremy.lucchetti@unige.ch.

[§]University of Lucerne, Department of Economics, P.O. Box 4466, 6002 Lucerne, Switzerland; phone: +41 41 229 5722; email: manuel.oechslin@unilu.ch. CentER, Tilburg University, The Netherlands.

1 Introduction

Over the past decade, understanding the determinants of internal conflict has become a central concern for academics and policy makers alike (see, e.g., Blattman and Miguel, 2010, for a detailed overview). So far, the literature has mostly focused on internal conflict between organized groups, for example on coups, rebellions, or revolutions.[1] Little attention has been paid, however, to other manifestations of internal conflict, in particular to riots. Contrary to coups, rebellions, or revolutions—where a potentially persistent fight occurs between at least two organized groups over the control of the state—riots are a violent and punctual disturbance to the public order by a crowd of individuals, for instance with the aim to show disaffection with a specific government decision. Riots therefore tend to flare up spontaneously and die down quickly.

This paper looks at the economic causes of rioting. Doing so is important for a variety of reasons. *First*, riots are a frequent form of internal conflict. In our dataset, which covers Sub-Saharan Africa in the period from 1990 to 2011, there are 1,738 recorded events of rioting (compared to 41 civil conflicts or wars, according to the UCDP/PRIO Armed Conflict Dataset). *Second*, rebellions or revolutions rarely start all of a sudden but are often preceded by a series of protests and riots. Thus, a better grasp of the triggers of riots may lead to a better understanding of the emergence of truly disruptive events like rebellions or revolutions. *Third*, riots are often associated with a high number of fatalities. According to the *New York Times* ("U.N. Raises Concerns as Global Food Prices Jump", September 4, 2010), two days of rioting in Mozambique in August 2010 left ten people dead and some 300 injured. About two years earlier, a number of "food riots" in Africa claimed many more lives (24-100 in Cameroon alone, according to a guess by Berazneva and Lee, 2013). Looking at our riot data, 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

[1] 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 (but not uncontested) definition, a conflict between organized groups is called a "civil conflict" if it causes at least 25 battle death in a single year and it is called a "civil war" if this number is greater than 1000 (see Blattman and Miguel, 2010).

the cost in terms of human lives, rioting is also costly in economic terms. Riots disrupt private economic activity and basic government functions; as a result, frequent rioting is a severe obstacle to economic development, particularly in poor places.[2]

The present paper investigates empirically the relationship between various measures of rioting and the current economic situation. When studying the causes of internal conflict, it is important to distinguish between different forms of violence. Civil conflicts are characterized by a persistent fight between at least two organized groups and hence involve significant organizational capacity, planning and funding. Riots, by contrast, are characterized by loose organizational structures rather than cohesive actor formation and organized warfare. We argue that this fundamental difference begs for a specific empirical treatment. A set of recent papers (Theisen et al., 2011; Harari and La Ferrara, 2013; Couttenier and Soubeyran, 2014; Hodler and Raschky, 2014) use geographically disaggregated data to explore the impact of climate shocks on conflicts between organized groups. They highlight the fact that civil conflicts are persistent and tend to diffuse spatially (see Harari and La Ferrara, 2013, for a recent empirical treatment of the temporal and spatial diffusion of civil conflicts). In sharp contrast to this pattern, our data suggests that riots are *short lived* and *confined* events. These characteristics, in combination with low requirements regarding organisation and funding, are likely to make riots more responsive to weather stress (and the associated income shocks).

Our empirical analysis is based on geographically and temporally disaggregated data from Sub-Saharan Africa.[3] 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 is unique in the literature and allows us to tackle the specificities of riots. These specificities appear clearly in the data. 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

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

[3]While the riot data cover the years 1990-2012, our main explanatory variable is only available until 2011.

a week. We further observe that riots are spatially confined 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 relationship we are interested in is the one between current economic circumstances and the level of rioting. By current economic circumstances we mean deviations of the actual income in a cell from the cell's "normal" income level, i.e., the income level that corresponds to the cell's potential. Since income data is not available at this high level of spatial/temporal resolution, we follow a reduced-form approach (as do, e.g., Harari and La Ferrara, 2013; Couttenier and Soubeyran, 2014; O'Loughlin et al., 2014). 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. The water balance matters primarily for vegetation activity: A lower balance reduces plant growth (Vicente-Serrano et al., 2012) and hence agricultural output. We therefore take SPEI as an indicator for the monthly (agricultural) income (above/below normal) generated in a cell. Moreover, by using additional cell characteristics—including the share of cropland and the amount of water available per capita—we are able to pinpoint the channel by which the water balance impacts rioting. Specifically, we find that a below-normal water balance has a far higher impact on rioting in agricultural zones characterized by relative water scarcity.

The fine temporal resolution also allows us to use a uniquely rich set of fixed-effects to control for, among other things, sub-annual time-varying (and potentially confounding) factors such as seasonal patterns.[5] Accounting for seasonal patterns is important. The

[4]Spatial issues become even less of a problem in our empirical analysis as we restrict our sample according to population size (see the discussion on the following page and in Section 3.2).

[5]By disaggregating our data to the monthly level, we differ from recent contributions (e.g., Theisen et al., 2011; Harari and La Ferrara, 2013; Couttenier and Soubeyran, 2014; Hodler and Raschky, 2014) which use geographically disaggregated data to explore the impact of climate shocks on conflict between

recent literature (e.g., Harari and La Ferrara, 2013) shows that considering the growing season of the main crop in a cell is key in explaining the response of civil conflict to weather stress. Our set of fixed effects controls for growing patterns, while avoiding potential problems related to the use of indicators that are based solely on the main crop in a cell. Among these problems are that there can be multiple growing seasons in a single cell if crops are diversified or planted at different points in the year.[6]

The raw version of our dataset covers all 0.5×0.5 degree cells in Sub-Saharan Africa. However, 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. Our baseline specification thus focuses on a sub-sample of cells with a population above a certain threshold (which is the 6th decile, evaluated at the country level). We do, however, provide estimation results for various alternative thresholds, including results based on 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 9th percentile, the corresponding number is 25.2 percent. We further investigate the circumstances under which the actual water balance is particularly important for the level of rioting. We show that a drop in SPEI has a much larger effect on rioting in cells with limited water availability—and an even larger effect in cells that combine limited water availability with relatively strong agricultural activity. These results suggest that shocks to the water balance affect rioting through agricultural incomes.[7]

This paper is related to a vast empirical literature on the impact of economic shocks, or shocks related to weather anomalies, on violent conflict (Miguel et al., 2004; Burke et al., 2009; Ciccone, 2011; Dell et al., 2014). By using a temporally and geographically disaggregated empirical strategy, and by relying on a drought index to proxy for weather

organized groups (at the yearly level). Our spatial resolution is also finer (0.5×0.5 degrees).

[6]Using data on growing patterns (HarvestChoice, 2010), we indeed find that more than 60% of the cells have at least two distinct growing seasons. That is, in more than 60% of the cells, there is a gap of 10 weeks or more between the earliest and latest start dates within a calendar year.

[7]We also consider a number of additional cell specifics that may amplify the effect of SPEI on rioting. Among other things, we find that proximity to urban areas significantly increases the impact of SPEI.

anomalies, our work has a close link to recent contributions by Theisen et al. (2011), Harari and La Ferrara (2013), Couttenier and Soubeyran (2014), and Hodler and Raschky (2014).[8] However, while all these papers focus on big 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). 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.

The rest of this paper is organized as follows. The upcoming section discusses potential linkages between income shocks and rioting 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

A riot is a contentious and violent action by a crowd of individuals against the government or another distinct group. Yet, in contrast to other forms of internal conflict, such as rebellions or revolutions, riots do not involve organized, armed violence but are more spontaneous in nature. It is natural to hypothesize that there should be a negative relationship between the level of rioting in a region and the current state of the region's economy. There are several channels by which a negative deviation of a region's current

[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 focus on riots is also one important factor distinguishing our study from a recent paper Wischnath and Buhaug (2014) who use subnational data from Indian states to explore how fluctuations in food production affect the severity of ongoing conflicts (as measured by fatalities or battle deaths).

output from its normal level may provoke riots. For instance, in agrarian economies, a fall in agricultural yields below the usual level may lead to tougher competition over access to water or land, potentially resulting in an outburst of violence between different competing groups (see, e.g., Hendrix and Salehyan, 2012). Butler and Gates (2012), studying 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. A sudden fall in (agricultural) output may also spark violence directed toward the government. Motivated by the observation that violent forms of tax resistance have a long tradition in Sub-Saharan Africa (see, e.g., Fjeldstad et al., 2014), an earlier version of this paper presents a rational rioting model in which ongoing riots make it harder for the government to impose onerous taxation. In this model, a fall in output below normal levels immediately sparks anti-government riots because of informational asymmetries that delay the government's fiscal response to falling incomes.[10]

Section 4 explores whether such a negative and immediate impact of agricultural output fluctuations 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 agricultural output from the normal cell output. 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 for the details). The reason is that 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 causal effect of agricultural output fluctuations on the level

[10]The above-mentioned rioting model differs substantially from models of internal warfare (e.g., Chassang and Padro-i-Miquel, 2009; 2010) or political transitions (e.g., Acemoglu and Robinson, 2001). While the latter two seek to explain big events like civil wars or democratic transitions, the rioting model aims to rationalize spontaneous clashes between rather unorganized crowds of citizens and the government.

of rioting, we need to address a number of issues. Most importantly, there are a two econometric problems that make it difficult to identify causal effects. *First*, there could be problems of reverse causality as the level of rioting may have an impact on economic activity. If the empirical measure of cell output reflects output net of rioting costs, an exogenous surge in the level of rioting (e.g., due to ethnic tensions unrelated to economic issues) reduces measured cell output. *Second*, cell output could be endogenous in the sense that there may be forces affecting output and rioting at the same time. Moreover, we cannot rule out that there are time-invariant cell characteristics that affect both output and unrest. *Finally*, there is an issue of data availability. Following a geographically and temporally disaggregated approach, the required output data is not available.

We deal with all of these issues by means of our set of explanatory variables. In particular, we use the Standardized Precipitation-Evapotranspiration Index (SPEI) constructed by Vicente-Serrano et al. (2010) to proxy for deviations of the actual agricultural output from the normal output.[11] SPEI is a drought index that reflects a cell's climatic water balance (see again Section 3 for the details). An index value greater (less) than zero indicates an above-normal (below-normal) water balance. As the water balance matters for agricultural output, we take SPEI as an indicator of the deviation of agricultural productivity—and hence agricultural output—from its normal level. Relying on SPEI is also a way of addressing the problems of reverse causality and omitted variables. More specifically, the level of rioting has no impact on the water balance, which suggests that reverse causality is not an issue when using SPEI. Moreover, 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 also control for other possible factors influencing 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 weather. We also rely on region-by-month fixed-effects to control for region-specific seasonal patterns in the data.

[11] So we perform a reduced-form analysis, as does much of the related conflict literature (e.g., Burke et al., 2009; Harari and La Ferrara, 2013; Couttenier and Soubeyran, 2014).

The inclusion of region-by-month fixed effects addresses in particular 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 probably do not occur at a frequency higher than yearly). In essence, by including a set of fixed effects that is unique in terms of richness, 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 the level of rioting to deviations of actual moisture conditions from normal levels (captured by SPEI). In particular, we estimate specifications that include an interaction term involving SPEI and a measure of average water availability in a cell; and specifications that include an interaction term involving SPEI and measures of both water availability and the prevalence of cropland in a cell. By including these interaction terms, we want to see whether a possible effect of SPEI on the level of rioting works through the agricultural output channel. If this were the case, the signs of the coefficients should be negative: Following the logic of diminishing returns, actual moisture conditions should matter more for the current (agricultural) output—and hence the level of rioting—in cells that are characterized by relative water scarcity; similarly, moisture conditions can be expected to have a stronger effect on the current state of the econony (and hence rioting) if the agricultural sector is relatively important. We also 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, 2013; Hodler and Raschke 2014) in relying on a linear probability model when using a binary dependent variable.[12]

3 Data

3.1 Data Sources and Descriptive Statistics

Our empirical analysis relies on several data sources. The information used to construct our dependent variable 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.[13] 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 unrest events 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 dif-

[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 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. *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 (2013) show that this can cause biased results in a nonlinear setting.

[13]The database can be accessed through the website *www.scaddata.org*. See the codebook, which is posted on the website, for a full description of the database.

ferent 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 on 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 an agriculture-relevant drought index, the so-called Standardized Precipitation-Evapotranspiration Index (SPEI), which was developed by Vicente-Serrano et al. (2010). SPEI reflects the climatic water balance at different time scales. We consider the monthly climatic water balance, i.e., the monthly difference between precipitation and potential evapotranspiration (using SPEIbase V2.2). The climatic water balance is an important factor affecting vegetation activity and, as a result, agricultural productivity. 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 sub-humid conditions, i.e., under conditions one finds 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). The growing and harvest season therefore tends to cover a large part of the year, implying that moisture conditions matter throughout the year as well.

Importantly, SPEI is a standardized variable. It expresses the climatic 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. This standardization, and the fact that the water balance matters for agricultural productivity for the most part of the year, makes the index particularly well suited for the present context: Deviations of SPEI from zero can be interpreted as deviations of the actual agricultural output from the normal agricultural output; moreover, given that the agricultural sector has typically a significant weight in Sub-Saharan economies, SPEI can also be regarded as a proxy for deviations of the actual total cell output from its normal level.[14]

By using a drought index, instead of just rainfall and/or temperature, we follow the recent literature on climate and conflict (e.g., Harari and La Ferrara, 2013; Couttenier and Soubeyran, 2014). One of the concerns with rainfall as such is that it is not a priori clear how and to what extent precipitation affects agriculture. For instance, the impact of precipitation on agriculture depends also on the degree to which water is retained by the soil. The capacity of the soil to retain water, in turn, depends on a variety of factors, including most notably surface temperature, but also air humidity, sunshine exposure, latitude, and wind speed. Drought indices like SPEI or PDSI (which is used by Couttenier and Soubeyran, 2014) incorporate this information. We chose to use SPEI because of its higher level of disaggregation. Given that we consider riots (which are more frequent and more localized than conflicts between organized groups), the high level of spatial and temporal disaggregation is an important part of our empirical strategy.[15]

In addition to relying on SCAD and the SPEI database, we work with a variety of other data sources. Most importantly, we rely on data (available at the subnational level) provided by Gassert et al. (2013) and Ramankutty et al. (2008) to explore whether the impact of SPEI on the level of rioting possibly works through deviations of the actual agricultural output from the normal one, 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 co-authors provide information on the total quantity of water available to catchment in a cell (before any uses are satisfied). In brief, water availability (measured in m^3) is calculated as all water flowing into catchments from upstream catchments (net of estimated upstream consumption) plus any imports of water to the catchments.

We further rely on population data (Tollefsen et al., 2012; "PRIO-GRID") because we

[14]In the average Sub-Saharan economy, agricultural output accounted for about one third of the GDP in 1990 and for about one fourth in 2010, according to data from the World Development Indicators (http://data.worldbank.org/data-catalog/world-development-indicators). For the year 1990, FAO data (http://faostat.fao.org) classifies about 65% of the total population in Sub-Saharan Africa as agricultural population (for the year 2010, the corresponding number is 55%).

[15]Riots are local in nature and tend to die down quickly. As a result, they are also less likely to disturb the gathering of data in the field (especially rain data at the gauge station). This is a potential issue for more intense and longer forms of internal conflict.

restrict our empirical analysis to areas with a certain population density. 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 proportion of area 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; the level of ethnic fractionalization; and, for some robustness checks, the distance to the national capital.

To account for the main growing season in a cell, we use growing seasons surfaces derived specifically for Sub-Saharan Africa by HarvestChoice (2010). HarvestChoice use 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 10km$\times$10km 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 season). The annual values were then compared to determine a representation of the start and end dates of the growing season for a given pixel.[16] 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).[17] 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 (and equal to zero otherwise).

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, 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.

[16] 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).

[17] 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	Mean	Std. Dev.	Min.	Max.	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 on riot is observed in t, but none in t - 1; SPEI: Standardized Precipitation-Evapotranspiration Index; Water: available water per capita (m^3/N); 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.

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 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 been 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

Table 2: Descriptive Statistics based on population deciles

Decile	N (cells)	Rioting	SPEI	Cropland	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.

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 populations restrictions, including the results we obtain when using the full sample. The quantitative impact of SPEI on all measures of riots rises monotonically with population size.

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.[18] 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 moisture conditions on the current level of rioting, we

[18] 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

	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	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 on 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.

are also interested in the mechanism linking the two variables. If deviations of actual moisture conditions from normal levels affect rioting through their impact on agricultural output, as hypothesized in Section 2, we suspect the impact of SPEI on rioting to be stronger in cells with a comparatively low availability of water and a high significance of agriculture. Table 4 presents several specifications testing for the presence of such interaction effects. Columns 1–9 of Panel A show results when we include an interaction term SPEI×Water(xth), where Water(xth) is a dummy variables that equals one if water availability (in per-capita terms) is below the xth percentile of our restricted sample, where $x \in \{50, 25, 10\}$. We observe that water scarcity significantly increases the effect of SPEI on riots, with the size of the increase rising in water scarcity. For instance, the estimated effect of SPEI on Inc in cells below the 25th percentile is more than three times larger than the corresponding baseline estimate presented in Table 3, Column 2.

Panel B of Table 4, on the other hand, addresses the question whether the effect of SPEI on riots is even stronger in cells characterized by a combination of water scarcity and substantial agricultural activity. Columns 1–9 show the results based on specifications that include interaction terms 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—the effect of SPEI on riots is larger in cells that combine water scarcity with a relatively substantial share of cropland; moreover, the increase in the impact of SPEI is rising in the prevalence of cropland.[19] Finally, a comparision of Panels A and B shows that—relative to cells with 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. In sum, the findings presented in Table 4 are clearly supportive of the conjecture that moisture conditions (as captured by SPEI) impact the level of rioting through the agricultural output channel.

[19]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

	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	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

	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	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) &	-0.00402	-0.000909	-0.000703						
×Crop(10th)	(0.131)	(0.041)	(0.088)						
.×Water(10th) &				-0.00439	-0.000977	-0.000754			
×Crop(25th)				(0.132)	(0.045)	(0.094)			
.×Water(10th) &							-0.00573	-0.00114	-0.000820
×Crop(50th)							(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.

4.2 Further Interactions

Besides water scarcity and the prevalence of cropland, there may be other important factors influencing to what extent moisture conditions affect the probability of riots. It is the purpose of this subsection to empirically explore further interaction effects. Following Harrari and La Ferrara (2013), 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 moisture conditions may have a stronger effect on agricultural yields, and hence on riots, within the average growing season than during the rest of the year. This is, however, not the case in our data: The interaction SPEI$\times$Growing Season is insignificant (while SPEI remains significant), as can be seen from Columns 1–3 of Table 5. 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.[20]

We are also left with insignificant results when we aggregate our dataset on a yearly level in order to use a specification that is similar to Harrari and La Ferrara (2013). The results can be found in Column 4 (restricted sample) and Column 5 (full sample) of Table 5. We suspect that this difference between riots and civil conflicts stems from the fact that civil conflicts and riots are very different in nature. In particular, riots are short-lived events which flare up immediately in response to a stimulus—which speaks in favor of using monthly data when studying this type of internal conflict.

Table 6 reports results for specifications that include further plausible interaction terms, 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

[20]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 5: Interaction effects: Growing season

	NoD	Inc	Ons	Inc	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 (2013), 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 month for which the SPEI is below this threshold.

mean of our sample); the interaction between SPEI and the dummy variable "Ethnic Fractionalization" (equal to one if the number of ethnic groups in a cell is above the average number of ethnic group in 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 6 do not suggest that a comparatively high prevalence of irrigation systems would mitigate the impact of SPEI. An 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). On the other hand, we do find some weak evidence indicating that the effect of SPEI is larger in cells with a comparatively high level of ethnic fractionalization (Columns 4–6 of Table 6). This result is reminiscent of a recent finding by Couttenier and Soubeyran (2014) which suggests that the impact of droughts on the risk of civil war is stronger in countries that are more ethnically fractionalized. Finally, Columns 7–9 of Table 6 suggest that SPEI has a stronger effect on rioting in cells where the average travel time to the closest urban area is relatively short. This result is consistent with the view that urban areas provide fertile ground for riots as they facilitate the formation of crowds and tend to host "popular" targets (such as the seats of government agencies).[21]

4.3 Robustness

Tables 7 to 11 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 7 shows results when we control for the potential persistence of the dependent variable,[22] 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 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.

[21] We also estimated specifications with interaction terms involving: SPEI and the distance of the cell to the country's capital city; and SPEI and the Polity2 index from the Polity IV Project (data aggregated at the country-year level, see Table 12 in the appendix). Both interaction terms are insignificant.

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

Table 6: Interaction effects: Irrigation, ethnic fractionization, and distance from an urban center

	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	Ons
SPEI	-0.000349	-0.0000980	-0.0000867	0.000330	-0.0000757	-0.0000893	-0.0000557	-0.0000622	-0.0000702
	(0.276)	(0.256)	(0.262)	(0.243)	(0.254)	(0.140)	(0.768)	(0.092)	(0.048)
.×Irrigation	-0.00120	-0.000114	-0.0000596						
	(0.380)	(0.585)	(0.744)						
.×Ethnic Fractional.				-0.00130	-0.000161	-0.000159			
				(0.028)	(0.168)	(0.146)			
.×Urban Area							-0.00634	-0.00146	-0.00134
							(0.096)	(0.033)	(0.031)
N	421741	421741	421741	583930	583930	583930	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 and ethnic fractionalization dummies are equal to one if the underlying variable is larger than the mean of the restricted sample. The urban center dummy is equal to one if the travel time to the nearest urban center is less than two hours.

The baseline results are again confirmed when we estimate a standard first-differenced (fd) specification, as shown in Columns 1–3 of Table 9. 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 9).

Table 10 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 10 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 11 reports results based on non-linear specifications, namely Negative Binomial and Logit. These estimations are consistent with the results in the previous tables: A negative agricultural shock 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

Anecdotal evidence suggests that violent riots, which are a widespread phenomenon in poorer places, disrupt commerce and basic government functions. Frequent outbursts of riots are therefore a serious obstacle to economic growth in developing countries. Our data from Sub-Saharan Africa suggest further that riots are also costly in terms of human lives. Over the 1990–2012 period, the average riot was associated with 66 fatalities. Although riots matter, the internal-conflict literature has so far almost exclusively focused on explaining conflict between organized groups, such as coups, rebellions, or revolutions. This paper, by contrast, explores some possible triggers of riots. In particular, it empirically investigates how the level of rioting in a certain area is affected by the current economic situation. A plausible hypothesis is that a negative (positive) deviation of the current output from its normal level raises (reduces) the level of rioting.

Our empirical strategy is precisely tailored to the phenomenon we study. Unlike civil conflicts, riots are temporally and geographically confined events. We accommodate these specifics by relying on highly disaggregated data (monthly, at the 0.5×0.5-degree cell level). As output data at such a high resolution is unavailable, we use the SPEI drought index—which can be viewed as an indicator of agricultural productivity—to proxy for deviations of the actual output from normal levels. Moreover, we rely on a rich set of fix effects, a strategy that makes it highly plausible that any effect of SPEI on the level of rioting is in fact causal. We further contribute to the literature by exploring whether deviations of the water balance from normal levels have a larger effect on rioting in cells that are characterized by water scarcity and a substantial share of cropland.

Our estimates indeed suggests that the level of rioting is high (low) if the actual agricultural output is below (above) the normal one. 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. We further find that a drop in SPEI has a much larger effect on the level of rioting in cells in which water is relatively scarce—and an even larger effect in cells that combine water scarcity with a relatively substantial share of cropland. These findings support the conjecture that moisture conditions (as captured by SPEI) affect rioting through the agricultural output channel. Similarly, we find that proximity to urban areas significantly increases the impact of SPEI, a finding that is consistent with the view that urban areas make flocking together easier and offer a larger number of suitable targets.

By exploring the triggers of violent 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 7: 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 8: Estimation results for different sample restrictions

	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	Ons
spei	-0.000134 (0.293)	-0.0000397 (0.078)	-0.0000448 (0.028)	-0.000126 (0.347)	-0.0000474 (0.052)	-0.0000511 (0.021)	-0.000136 (0.369)	-0.0000537 (0.048)	-0.0000582 (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 (0.378)	-0.0000641 (0.039)	-0.0000692 (0.014)	-0.000158 (0.454)	-0.0000735 (0.040)	-0.0000796 (0.014)	-0.000263 (0.174)	-0.0000968 (0.019)	-0.000103 (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 (0.105)	-0.000168 (0.009)	-0.000173 (0.003)	-0.000537 (0.119)	-0.000247 (0.008)	-0.000245 (0.003)	-0.000997 (0.107)	-0.000480 (0.006)	-0.000437 (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 for first-differenced specifications

	NoD, fd	Inc, fd	Ons, fd	NoD	Inc	Ons
SPEI, fd	-0.000472 (0.037)	-0.000191 (0.006)	-0.000189 (0.004)	-0.000156 (0.276)	-0.000110 (0.006)	-0.000113 (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 10: 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 11: 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.

Table 12: Distance to the capital and Polity II index

	NoD	Inc	Ons	NoD	Inc	Ons
SPEI	-0.000108	-0.0000491	-0.0000849	-0.000116	-0.000107	-0.000133
	(0.648)	(0.368)	(0.124)	(0.619)	(0.180)	(0.075)
.× distance to the capital	-0.000389	-0.000129	-0.0000769			
	(0.282)	(0.141)	(0.350)			
.× Polity2				-0.000418	-0.0000423	-0.00000293
				(0.350)	(0.665)	(0.973)
N	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. Both dummies (distance to capital and Polity2) are equal to one if the underlying variable is larger than the mean of the restricted sample.