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Reexamining the Role of Income Shocks and Ethnic Cleavages on Social Conflict in Africa at the Cell level

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Abstract: This paper reexamines the effect of exogenous income shocks and ethnic diversity on social conflict in Africa. Unlike previous literature, we jointly consider geolocalized information on three types of shocks (agricultural, mineral, and oil and gas price changes) and four measures of ethnic diversity (fragmentation, polarization, and both monopoly and excluded power of polity groups). With this approach, we can give a more complete vision of the determinants of violence. We find that the impact of income shocks is heterogeneous across conflict definitions and ethnic diversity measures. In particular, positive agricultural and mineral price shocks increase the probability of social conflict, riots, and violence across civilians in general, but decrease the incidence of armed conflict. Oil and gas price shocks, on the other hand, do not show significant direct effects. In addition, cells in which monopoly or excluded ethnicity are present tend to produce higher levels of violence. We also look at the interaction between income shocks and ethnic diversity; the results imply that the existence of extreme cases of political-power differences among ethnic groups reduce the positive impact of income shocks on the probability of conflict, whereas ethnic fractionalization always raises it. Comparing to the prevailing theories in the literature, our findings suggest that the direct effect of price shocks on armed conflict and general conflict are driven by opportunity costs and by the desire of political change, respectively, whereas their interacted effects with ethnic diversity depend on state capacity.

Keywords: conflict, income shocks, food security, natural resources.

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1 Introduction

The risk of a food crisis is one of the most important issues that is faced by society. Indeed, 108 million people in the world were living at risk of hunger in 2016 (Nkunzimana, 2017). Consequently, understanding the determinants of food insecurity is an important objective that investigators have integrated into their research agendas. Social conflict is without any doubt one of these determinant, a leading cause of hunger and general food insecurity in several parts of the world; conflict causes disruptions in food production and distribution, unemployment, human capital loses, reductions in wages and income, and displacements of the population. This paper investigates factors that affect conflict, in the African continent, a very vulnerable part of the world with a relatively low capacity of adaptation. In fact, Africa is the region most affected by conflicts after the Second World War. In early January of 2016, twenty-eight countries and 201 militias-guerrillas, separatist and anarchic groups were involved in conflicts.

More specifically, we answer the following questions. How do the diversity and political status of ethnic groups and income shocks affect social conflicts? Does the ethnic structure of the society influence the impact of income shocks? We argue that these effects differ across societies and conflict definitions. Unlike previous literature, we work with a full grid of African countries divided into sub-national units of 0.5 x 0.5 degrees latitude and longitude, disaggregate income shocks in agricultural, oil/gas and mineral, and consider different measures of ethnic status, namely, spatial polarization and fragmentation, and monopoly and excluded political power. Our approach exploits exogenous sources of variation in income shocks related to the non-predictable component of international commodity prices. We also incorporate climate into the regressions, another factor that influence the supply of food.

The impact of income on conflict has been widely studied in the literature.[1] A common approach has been to employ external shocks captured by fluctuations in commodity prices in order to isolate the effect. At the country level, results have been mixed. For example, Bersley and Persson (2008) find a positive relationship between income shocks and conflict, whereas Brückner and Ciccone (2010) find the opposite. Bazzi and Blattman (2014) disaggregate shocks into agricultural and extracted industries, and argue that a significant relationship between commodity prices and conflict incidence can only be detected in specific cases. At the micro-level, on the other hand, the analysis points out a more robust causal relationship. For instance, Dube and Vargas (2013), Fdjelde (2015), and Berman et al. (2017) find that agricultural price shocks are negatively correlated with conflict, whereas mineral and oil prices are positively correlated.

More recently, using geocoded data, McGuirk and Burke (2017) have tried to reconcile the ambiguous results found at the country level on the economic roots of conflict focusing on agricultural-type shocks. They differentiate between two sources of violence. First, factor conflict in food-producing cells, where higher prices reduce civil conflict battles over the control of territory. Second, output conflict within consumption cells, where there is smaller-scale conflict over the appropriation of surplus. They find that only in the latter type of conflict income-shock effects are positive.

[1]The main motivation is that the association among low economic growth and violence, and the impact of the latter on mortality are among the most consistent and robust findings in the literature. See, for example, Collier and Hoefler (2004) and Hegre and Sambanis (2006)

Economists have also emphasized the role of ethnic diversity on the generation of violence, like ethnic fractionalization and ethnic polarization in civil wars in Montalvo and Reynal-Querol (2005), Esteban and Ray (2008 and 2011) and Esteban et al. (2013), among others. In turn, political science papers such as Cederman et al. (2009) and as Cederman et al. (2011) have also studied the importance of the presence of ethnic groups excluded from political power and ethnic groups that enjoy monopoly over the state. Unlike these papers, we study the role of ethnic status in the propagation of income shocks that affect the incidence of conflict, and consider those measures of ethnic diversity all together.

The interest for understanding this interaction is not completely new; it has been analyzed by Janus and Rivera-Crichton (2015), but at the country level, focusing on the onset of conflict instead of its incidence, employing fully aggregated price shocks, and considering only ethnic polarization and fragmentation.[2] We change the level of observation and consider additional variables. More specifically, our analysis concentrates on a grid-country cell level, combining sub-national, time-invariant maps of crop productions and oil and gas fields and time-variant mining activity, with information on the movement of global commodity prices and the four different ethnic-status variables mentioned previously. We also make a step forward by introducing the spatial ethnic fractionalization index developed at the cell level by Montalvo and Reynal-Querol (2017), by adapting the spatial ethnic polarization index to the cell level, and by extracting the non-predictable component (arguably more exogenous) of commodity prices using a regression approach.[3]

Our findings concerning the direct effects of income shocks confirm the ones obtained by McGuirk and Burke (2017) for agricultural prices: the sign of these effects depend on the definition of conflict adopted. Increases of both agricultural and mineral commodity prices lead to a rise in social riots, violence against civilians and social conflict in general, supporting theories that emphasize that a decrease in real income or an increase in the prize of success (the so called rapacity effect) fuels rebellion. However, we find that there is no impact of changes in oil and gas commodity prices on these variables. When, on the other hand, armed force is employed to measure violence, with at least 1 death at a specific location and a specific date, an increase in agricultural prices leads to a decrease of organized conflict, whereas mineral price shocks have no effect. This last result supports the idea that agricultural price shocks increase the opportunity cost of joining armed conflict thus decreasing violence.

Looking at the effect of the political power of ethnic groups, we find that the presence of extreme cases raise the probability of conflict. In particular, cells that contained ethnic groups with monopoly or excluded political power are associated with larger levels of violence, independently of the conflict measure. Results also point to strong interaction effects of income and ethnic variables. More specifically, a larger degree of ethnic polarization and both excluded and monopoly groups reduce (i.e., makes it less positive or more negative) the impact of income shocks on all types of conflict; whereas a larger degree of ethnic fractionalization raises it. The interaction effects are weaker for income shocks related to extracted industries than to agriculture. All these findings are robust to

[2] In addition, Brückner and Gradstein, (2015) find that the likelihood of a coup, revolution, civil conflict and civil war induced by oil price windfalls decreases in countries with low level of ethnic polarization.

[3] Several African nations produce a large volume of commodity output, leading to a potential endogeneity problem related to prices (Bazzi and Blattman, 2014). For example, from the supply side, a conflict could lead to reduced production, and hence, increase commodity prices. We prevent possible endogeneity issues by taking the error term associated to predicting prices employing up to three year lags.

a variety of consistency checks.

The rest of the paper is organized as follows. Section 2 reviews several mechanisms proposed in the literature to justify a possible connection of commodity price shocks and ethnicity with social conflict. The data and the econometric methodology are presented in Sections 3 and 4, respectively. Section 4 shows our main results. The conclusions are discussed in section 5.

2 Theories of Social Conflict

There exist several competing theories of the effect of income shocks on social conflict. One of them is the opportunity cost theory. In economic analysis, rational individuals weight the relative returns, costs, and risk for choosing between to produce or predate (Becker, 1968). In fact, models of rebellion suggest that civilian's incentives to rebel rises as economic opportunities and household income decline (Grossman, 1991), due to an opportunity cost effect. In the case of oil and mineral, the profits from these capital-intensive commodities are collected mainly by the state, and therefore, revenues from this type of commodities affect income through public goods and transfers. In the case of agriculture, the opportunity cost theory predicts a strong inverse relationship between the prices of its crops and conflict. (Dal Bò and Dal Bò, 2011).

A second one, based on the state-is-a-prize mechanism, suggests that rents depend on both the value of natural resources and the feasibility of capturing such rents. This value varies with both the stock of natural resources and their prices. In turn, capital-intensive commodities such as minerals and oil and gas are more prone to be taxable than the agricultural ones, and hence, can be more easily captured. Predictions of the state-is-a-prize theory then suggest that rising prices should increase the risk of insurrection as a mechanism to capture rents, especially in the case of mineral and oil and gas.

We can point out a third mechanism to motivate the impact of income shocks on social violence: the state capacity theory. According to Ross (2012), for example, rising rents provide the state with a stronger capacity to buy off the opposition, and therefore, to prevent social conflict. In addition, more resources allow the state to counter insurgents and strengthen control. Predictions based on the state capacity mechanism are the opposite to the ones from the state-is-a-prize theory: the former implies that rising oil and mineral prices can lower the probability of social conflict.

Moving now to the impact of ethnic diversity, papers such as Blattman and Miguel (2010) have emphasized ethnic nationalism as a preeminent source of group cohesion.[4] Because of this, some theoretical studies suggests that ethnic heterogeneity is detrimental for public policies and development (Alesina et al., 1999). Consequently, the index of fractionalization as a measure of diversity has been used in several empirical studies of conflict with the idea that ethnically diverse societies have a higher probability of ethnic

[4]Economics models that assume that co-ethnic preferences can enlarge intra-groups mechanisms of cohesion and communication are following the "primordialist" arguments developed by Horowitz (1985). In the "primordialist" theory, conflict is rooted in intense emotional reactions based on deep biological, cultural or psychological nature of ethnic cleavages (Alesina et al., 1999; Alesina and La Ferrara, 2000; Esteban and Ray, 1999). Nevertheless, even if ethnic identity is not considered as primordial, ethnic groups often create dense social networks and low-cost information and sanctioning (Blattman and Miguel, 2010).

conflicts (Collier and Hoeffler, 2004; Fearon and Laitin, 2003; Miguel et al, 2004). Results from many of these empirical studies are surprisingly murky because there is not a strong relationship between ethnic fractionalization and civil wars. This motivated Esteban and Ray (1994) to develop a measure of ethnic polarization. Whereas ethnic fractionalization measures the probability that two randomly selected individuals from a given country do not belong to the same ethnic group, the polarization index assesses how far the distribution of the ethnic groups is from a bipolar distribution. Papers like Montalvo and Reynal-Querol (2005) have found polarization as significant to explain the incidence of civil war.

Finally, political sciences have emphasize the potential importance of ethnic political diversity in the incidence of conflict. For example, some of them find at the national level that the political marginalization of ethnic groups can lead to a strong motive for the rank-and-file grievance (Gurr, 1970; Horowitz, 1985) and to violence (Baseadu and Pierskalla, 2014; Cederman et al., 2009, 2010, 2011; Wimmer et al. 2009). In this paper, we consider two variables: excluded groups from the central power, and monopoly groups. Excluded groups are defined as relevant ethnic communities that are excluded from government relevant processes, whereas monopoly groups mean that elite members hold monopoly power in the executive that leads to the exclusion of members of other ethnic groups. Both excluded and monopoly ethnic groups can or cannot be at the same cell at a given point in time.[5] Few papers have used these variables in a grid-panel data context, and never in conjunction with other measures of ethnic diversity. Basedau and Pierskalla (2014) examine the role that the natural resource stock of oil and gas, and the political ethnic status play in conflict; and Uexkull et al. (2016) focus on politically-relevant ethnic groups and their sensitivity of growing-season drought on civil war.

Another key aspect that we analyzed is whether a plausible effect of ethnicity on conflict can be indirect (Bruner and Gradstein, 2015). That is, a positive income shock might have a different impact depending on the degree of ethnic diversity. For example, a positive agricultural shock can decrease the probability of incidence of conflict because of the opportunity cost mechanism. However, if trade among different ethnic groups involves monitoring costs because of the lack of trust between them, the impact of the income shock will be smaller in cells with a higher degree of ethnic fragmentation. A second example can be related to ethnic political power. In particular, the presence of monopoly groups might exacerbate income inequality within the cell, thus reducing the opportunity cost of poor individuals, or allow the dominant tribe to control natural resources that can provide the means to repress military threats or buy peace. Nevertheless, Baseadu and Pierskalla (2014) argue that groups that monopolize or dominate the state, and consequently their profits from resources, are likely to be threatened by relatively deprived groups. Excluded groups, on the other hand, are more likely to reside in the state periphery, and therefore, ethnic geography may be correlated with economic activity (Fdjelde, 2015). Furthermore, as Uexkull et al. (2016) point out, these last groups are more likely to be excluded from government-sponsored compensation programs, or even aid in the case of negative income shocks due to natural disasters (e.g., floods and severe droughts).

In summary, the type and degree of ethnic diversity can affect the impact of income shocks on the probability of social conflict, but the direction of this effect is uncertain (Basedau and Pierskalla, 2014). It will depend on how ethnic diversity alters the state

[5] As we can see in Figure 3 in Appendix B, most African countries have excluded ethnic groups, whereas only Angola, Mali, Rwanda, Libya, and Egypt have settled monopolist ethnic ones.

capacity, state-as-a-prize, and opportunity costs effects.

3 Data

Our baseline unit of analysis is a full grid of Africa divided into sub-national units of 0.5 x 0.5 grades latitude and longitude (which corresponds to a cell of roughly 55 x 55 kilometers at the equator). This is the result of intersecting a grid of 10,638 cells provided by PRIO-GRID (http://www.prio.no/Data/PRIO-GRID/) with a map of the entire Africa and their national political borders provided by the Global Administrative Unit Layers (2010), a project from the United Nations Food and Agricultural Organization (FAO). From the PRIO-GRID database, we download most of our non-conflict variables. The level of aggregation is the cell-year rather than ethnicity or administrative boundaries, in order to ensure that our unit of observation is not endogenous to social conflict events. It also mitigates issues of potential measurement error in the geo-location of the data and social conflict events. The sample coverage goes from 1997 to 2014 when conflict data comes from the Armed Conflict Location and Event Dataset (ACLED), and from 1990 to 2014 if the conflict numbers are taken from the Uppsala Conflict Data Program Georeferenced Event dataset (UCDP-GEO). In the rest of this section, we present the definition and sources of all variables employed in our regressions; Appendix A provides this information in more detail.

3.1 Conflict data

As mentioned above, we use two different datasets containing the geo-location of social conflict events in Africa: UCDP-GEO, version 5.0 (Croicu and Sundberg, 2016), and ACLED (Raleigh et al., 2017). The data cover different countries and time periods. Events are collected from various sources, that include humanitarian agents, research publications, or local, regional or international press news. As will become evident, the use of different dataset allows us to test different competitive theories and the robustness of our results. both datasets choose the event as the unit of observation, and contain information of the latitude and longitude, and (in the most cases) the precise day of conflict events. UCDP defines an event as an incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date. In addition, UCDP collects only information about organized armed groups that have fought in battles that directly caused at least 25 fatalities over all the period of the dataset. Events are included for the entire period, that is, both for the years when such conflicts were active (years that have crossed the 25 battle-related deaths threshold) and for the years when such conflicts were not active (the remainder). Our UCDP conflict-incidence variable includes three types of organized violence: state-based conflict, non-state conflict, and one-sided violence.

ACLED, in turn, registers a range of violent and non-violent actions by political agents, including governments, rebels, militias, communal groups, political parties, rioters, protesters, and civilians. The ACLED dataset has a broader perspective and records violent activity both within and outside the context of a civil war, and does not require any battle-related deaths threshold. In particular, we will later use as dependent variable three ACLED aggregates: overall incidence, battles, and social unrest; the latter contains the categories riots and violence against civilians.

Following Berman et al. (2015, 2017) and McGuirk and Burke (2017), we aggregate to the cell-year, coding with a value of 1 if cell c experienced a conflict during the year, and zero otherwise. This dummy represents our conflict-incidence variable. Table 1 presents summary statistics for the ACLED and UCDP measures of conflict-incidence. The unconditional probability of observing at least one UCDP conflict event in a given cell-year is low: 2.5% during the period 1990-2014. However, the standard deviation equals 0.156, a relatively large number. The unconditional probability of observing at least one ACLED conflict incident in a given cell-year is higher, 8.2%, and its standard deviation equals 0.274. In addition, when we constrain ACLED data to battles, the probability is around 4.1% with a standard deviation at 0.197, whereas ACLED riots and violence against civilians have an unconditional probability of 6.5% with a large standard deviation of 0.246.

Table 1: Basic statistics conflict variables

Variable	Obs	Mean	Std. Dev.	Min	Max
UCDP incidence	265800	.025	.156	0	1
ACLED_incidence	191376	.082	.274	0	1
ACLED battles	191376	.041	.197	0	1
Riots and Violence against civilians	191484	.065	.246	0	1

Because conflicts are highly persistent, both current and lagged conflicts can be correlated to current and lagged shocks. This is especially true at the country level. At a cell level, however, conflicts are less persistent; as Berman and Couttenier (2015) argue, about 75% of conflict events do not last more than 2 years. Nevertheless, following Berman and Couttenier (2015), and McGuirk and Burke (2017), we explore the robustness of our results to using conflict onset and conflict offset as dependent variables, because they do not suffer from this potential problem. More specifically, we define onset as $Conflict_{c,t} = 1$ conditioned on $Conflict_{c,t-1} = 0$, where c is the cell. Conflict offset is defined as $Conflict_{c,t+1} = 0$ conditioned on $Conflict_{c,t} = 1$. These definitions are equivalent to measuring the additive inverse of the persistence probability (McGuirk and Burke, 2017). The onset variable is coded as 1 on the onset of the conflict, and 0 otherwise. The offset variable, on the other hand, takes on 0 if a specific conflict event is going on and 1 in the year when that conflict ends, in all other years the variable considers that there are missing data.

3.2 Commodity price shocks

Our identification strategy is based on the use of the unpredictable component of commodity price changes as our proxy for economic shocks. Next we explain how we construct them in each of the three sectors: agriculture, oil and gas, and mining.

Regarding the agricultural price shocks, we combine time-series data of international commodity prices from the International Monetary Fund (IMF) International Finance Statistics, with spatial time-invariant data of crops production patterns from the M3-Crops dataset (Monfreda et al., 2008).[6] We cover the following crops: banana, barley,

[6]Available at http://www.imf.org/external/np/res/commod/index.aspx and

cocoa, coffee, cotton, groundnuts, maize, oranges, olive oil, rice, soybeans, sugar cane, sunflower, tea and wheat. A disadvantage of these data is that they only include crop production for the year 2000. Following Fdjelde (2015), and Bruner and Ciccone (2013), we aggregate the monthly international commodity prices to an annual price series for each commodity, normalized to 1 in year 1990, that is, the first year for the conflict database. At each date t, the cell-specific price index in cell c (PI^A_{ct}) is the average across the $i = 1, .., n$ agricultural commodities of the international crop prices (P^A_{it}) weighted by the time-invariant crop production shares (w_{ci}); that is,

$$PI^A_{ct} = \sum_{i=1}^{n} w_{ci} P^A_{it}. \tag{1}$$

To calculate the local commodity price index for oil and gas, we first obtain geocoded data of the localization of oil and gas fields in Africa from PRIO-GRID v.1.2. Then we construct a dummy variable (e_{ci}) coded as 1 if oil ($i = 1$) or gas ($i = 2$) or oil and gas (($i = 3$)) are present in a cell. Finally, we combine this with the IMF data on world oil and gas annual prices to estimate a price index for cell c and time t (PI^E_{ct}) as follows:

$$PI^E_{ct} = \sum_{i=1}^{3} e_{ci} P^E_{it} \tag{2}$$

where e_{ci} is a gas or/and oil dummy variable for cell c, and P^E_{it} is the annual price series for oil if $i = 1$, for gas if $i = 2$, and the average of P^E_{1t} and P^E_{2t} if both oil and gas are found in the cell. The index is normalized to 1 in the year 1990.

A similar methodology is employed to compute the mineral commodity price index. Firstly, we merge the information from two databases: the Mineral Resources Data System provided by the United States Geological Survey, and the information on gems, diamonds and gold contained in the PRIO-GRID v.2.0 dataset. Following Berman et al. (2017), we define a dummy variable coded as 1 in cells where at least one mine has been registered as active in the period 1990-2014 after its discovery or known production, and 0 otherwise. Because we no not have data on international commodity prices of gems and diamonds, the dummy variables only capture the presence of other mines. Specifically, we cover the following minerals: bauxite (aluminum), coal, copper, diammonium phosphate, gold, iron ore, lead, nickel, manganese, phosphate, potash, silver, tin, uranium, and zinc. Notice that the mineral dummies are time-varying because not all mines have been discovered at the same time. We combine the dummies information with price series from the IMF, and the Global Economic Monitor (GEM) Commodities dataset provided by the World Bank (WB) to obtain the following mineral commodity price index (PI^M_{ct}):

$$PI^M_{ct} = \sum_{j=1}^{n} m_{cj} P^M_{jt} \tag{3}$$

where m_{ci} is a dummy variable of mineral-i mine-presence in cell c, and P^M_{jt} is the annual price for minerals produced in the mine j, and indexes at 1 in the year 1990. If we have more than one mine in a cell, m_{ci}=1/j.

http://www.earthstat.org/data-download/, respectively

Once we have built price indices for the three different types of commodities (agriculture, oil and gas, and minerals), we calculate the price shocks. For this, like Kinda et al. (2016),[7] we extract the unpredictable component (arguably more exogenous) related to the price index of commodities of type K in cell c estimating the following econometric model:

$$\ln\mathrm{PI}^{K}_{c,t} = \alpha_{c,0} + \alpha_{c,1}t + \sum_{p=1}^{n} \theta_{c,p}\ln\mathrm{PI}^{K}_{c,t-p} + \epsilon_{c,t} \tag{4}$$

Hence, the price shocks are the estimated residuals obtained from a regression of the logarithm of commodity prices on its lagged values (up to three) and a linear time trend.[8]

In some of the empirical estimations, we also employe a price index shock for all commodities considered together; what we call the total price shock (S^{T}_{ct}). This overall variable is calculated as follows,

$$S^{T}_{ct} = S^{A}_{ct} + S^{E}_{ct} + S^{M}_{ct}, \tag{5}$$

where S^{A}_{ct}, S^{E}_{ct} and S^{M}_{ct} represent the agricultural, extractive and mineral shocks, respectively. Ideally, each shock should be weighted by the share of its associated commodities in the cell's gross value added. This information about the shares is, however, not available.

3.3 Spatial Ethnic Diversity

Our next task is describing the construction of the four different ethnic diversity measures: ethnolinguistic fractionalization, polarization, monopoly groups, and excluded groups . We follow Montalvo and Reynal-Querol (2017) to compute the spatial ethnolinguistic fractionalization index (EF). Firstly, we use numbers from the Geo-referencing of Ethnic Groups (GREG) database, which provides the geospatial location of different ethnic groups. They rely on data and maps from the classical Atlas Narodov Mira (Anm, Bruk and Apenchenko, 1964). For each country cell, we use the percentage of land in which an ethnic group settles. In particular, the index takes the form.

$$\mathrm{EF}_c\text{= 1-}\sum_{i=1}^{N} \pi_i^2 = \sum_{i=1}^{N} \pi_i(1-\pi_i) \tag{6}$$

where π is the proportion of area that belongs to ethnic group i (for $i = 1, ..., N$).

The calculation of the spatial ethnolinguistic polarization index (EP), on the other side, follows Montalvo and Reynal-Querol (2005). In particular,

$$\mathrm{EP}_c\text{= }4\sum_{i=1}^{N} \pi_i^2(1-\pi_i). \tag{7}$$

The last two ethnic diversity measures differ in a key aspect: while fractionalization increases monotonically if existing ethnic groups are divided into smaller groups, polarization is maximized when there are precisely two equally large groups.

[7]In a recent working paper, Giménez and Zewdu (2016) use also the residual component of their price index to study the effects on conflict of social heterogeneity and price shocks at the country level

[8]Kinda et al. (2016) estimated the shocks including a quadratic time trend. We chose a linear trend specification because it provides a better fit.

Moving now to the spatial political ethnic diversity proxies, we control for both excluded and monopoly groups using dummy variables that reflect these political statuses. Excluded groups is based on the numbers directly supply by PRIO-GRID 2.0. Specifically, the excluded-group variable is coded as 1 if there is at least an excluded group in cell c, 0 otherwise. The monopoly group proxy is also coded as 1 if there is at least a monopoly group in cell c, and as 0 otherwise. To create this variable, we use the groups identifiers provided by Cederman et al. (2011), and match our grid structure with the information on the political status of monopoly ethnic groups from the Ethnic Power Relations (EPR) Dataset Core 2014.

3.4 Climate, socioeconomic, and geographic variables

We complete our model using time-varying controls for geographic, socioeconomic and climate characteristics that could affect social conflict, directly or indirectly. In particular, shock variables could be correlated with other cell-specific characteristics such as climate variables (in the case of agriculture), economic activity, or closeness to both artificial country borders and capital cities. For example, as Burke et al. (2015) and MacGuirk and Burke (2017) argue, local weather events in producer countries could generate a correlation between international prices and the error term if those events are linked to global weather patterns such as the El Niño-Southern Oscillation.

Following Uexkull et al. (2016), we use a group-aggregate drought index, given the dependence of agriculture on weather conditions. Firstly, we use the SPEI Global Drought Monitor, which offers near real-time information about drought conditions, combining both temperature and rainfall data. [9] This index is used because precipitation might not be an accurate measure of climate variation impacting agriculture. In addition, Following Uexkull et al. (2015) and Harari and La Ferrara (2015), we also consider in the robustness analysis a crop-specific climate shock, the SPEI Shock Growing Season, which captures low SPEI episodes occurring during the growing season of the main crop in a given cell.

In order to control for local economic activity, we introduce satellite night lights, which have been used recently by several scholars such as Michalopoulos (2012), Michalopoulos and Papaioannou (2013, 2014) and Alesina et al. (2016) to proxy for aggregate output levels. In particular, following Montalvo and Reynal-Querol (2017), we create our variable night lights per capita in cell c at date t (NL_{ct}) as follows:

$$\mathrm{Ln}(\mathrm{NL}_{ct})=\ln\left(\frac{0.1+nightlight_{ct}}{0.1+population_{ct}}\right) \tag{8}$$

The numbers for night lights come from the PRIO-GRID project, version 2.0, database, and measure the average night-time light emission, calibrated to account for inter-satellite differences and inter-annual sensor decay. The population variable is also provided by the PRIO-GRID project, 2.0, and equals the sum of the number of people within each cell. Population estimated are available every five years, and hence, we interpolate to fill the

[9] SPEI stands for Standardised Precipitation-Evapotranspiration Index. These data are provided by the PRIO-GRID project from the Global Precipitation Climatology Center. The SPEI Global Drought Monitor is based on the Thortnthwaite equation for estimating potential evapotranspiration (PET). According to Harari and La Ferrara (2015), PET depends on several factors, including most notably temperature but also sunshine exposure, latitude and wind speed.

missing years. In the regressions, the log of population is also employed as an independent variable to control for the total population in the cell.

Finally, we incorporate as regressors geographic variables that can be related to conflict. In particular, we include the distances to both the capital and border of the country. Geographic variables are also taken from the PRIO-GRID project 2.0.

4 Empirical methodology

The aim of the paper is to study the way in which commodity price shocks affect the likelihood of social conflict, taking into account the role that ethnic heterogeneity plays in this effect. In order to achieve this goal, we propose a cell-level fixed effects framework that takes the form:

$$Conflict_{c,t} = \beta' * S_{c,t-1} + \omega * X_{ct-1} + \lambda * M_{c,t-1} + \sigma' * S_{c,t-1} * X_{ct-1} + \phi' * S_{c,t-1} * M_{c,t-1} +$$
$$+ \nu' * S_{c,t-1} * EP_c + \tau' * S_{c,t-1} * EF_c + \delta' * Z_{ct} + \omega' * D_c + \alpha' * D_i + \theta' * D_t + \varepsilon_{c,i,t} \quad (9)$$

The variable $Conflict_{c,t}$ can capture, depending on the specific regression, the incidence, onset or offset of a conflict in cell c and time period t. The vector $S_{c,t-1}$ contains the commodity-price shocks that occur in cell c at time $t-1$. In the next section, we consider two cases, one in which $S_{c,t-1}$ equals the total shock, and another one in which $S_{c,t-1}$ is the vector of disaggregated shocks. The time-variant ethnic political variables are denoted by $X_{c,t-1}$ and $M_{c,t-1}$, and represent the excluded and monopoly group dummies, respectively. We also control for cell, country and time fixed effects with the the dummy variables D_c, D_i and D_t, respectively. Notice that the first two of those dummies capture time-invariant characteristics that explain social conflict, and therefore, subsume, among other things, the direct effect of the time-invariant variables that proxy for ethnolinguistic fractionalization (EF) and polarization (EP). The vector $Z_{c,t-1}$ contains the set of control variables. Finally, ε is the corresponding disturbance term.

As we can see in equation (9), a battery of specifications of social cleavages at the cell level are considered. A main objective of our study is to evaluate whether the effect of commodity shocks on social conflict depends on ethnic diversity.[10]

In equation (9), β captures the impact on social conflict of exogenous income shocks that originate from agricultural, oil and gas, and/or mineral commodity prices. The sign of the coefficient is theoretically ambiguous. Remember that, as we mentioned previously, a larger income might increase the opportunity cost of fighting through a rise on wages, but also the likelihood of social conflict because of the rising value of the state's resources. Furthermore, the sign of the coefficient also depends on the type of conflict. We might not find the same coefficient sign if we study social conflict in general than if we focus on civil war, battles or riots.

[10] On Appendix C, we present a battery of robustness checks, Table C1 to Table C7, obtained without ethnic variables interactions. We show that the introduction of the interaction terms does not change the qualitative results.

Focusing now on ethnic political variables, we expect that ω is positive, whereas the sign of λ is ambiguous. The presence of excluded ethnic groups on natural-resource abundant territories might indicate grievance as we have explained in section 2. In addition, if there is not an equal access to employment, the opportunity cost of getting involve in violent activities will also be lower. This is why we believe that ω is likely to be positive. Monopoly groups, on the other hand, hold the benefits from the state's resources, and therefore, are likely to be challenged by relative underprivileged groups (Basedau and Pierskalla, 2014); because of this, λ should be positive. Nevertheless, the control of the income gains allows monopoly groups to sustain a powerful security apparatus (Le Billion, 2001b; Basedau and Pierskalla, 2014), buy-off support in the population, and attract the so called "greedy outsiders" that support the regime; thus making the sign of λ tend to be negative.

The set $Z_{c,t-1}$ besides containing the climate, socioeconomic and geographical factors that can influence social conflict and that we have described previously, also includes two interaction terms. One is the product of the excluded-group dummy and the drought index. This is motivated by the work of Uexkull et al. (2016) who show a relationship between droughts and excluded groups. In particular, they find that an increase in the number of consecutive years of drought during the local growing season, through their effect on agricultural income, raises the estimated probability of conflict for the average excluded groups. Nevertheless, their analysis is different from ours, because they concentrate exclusively on the dependence of climate and the agricultural output levels. The other interaction term incorporated in $Z_{c,t-1}$ is the product of the the excluded-group and the mine-presence dummies. This is based on the results found by Basedau and Pierskalla (2014) that support a relationship between natural resources and the political status of ethnic groups. We do not include an interaction term between the oil-and-gas and excluded dummies because of the time-invariant nature of the former.

Equation (9) is estimated as a fixed effect linear probability model (LPM). We prefer this estimator to the fixed effects conditional logit (CL) because we need a clear interpretation of the sizes of the coefficients. Following Berman et al. (2017) and Montalvo and Reynal-Querol (2017) the coefficients' standard errors are estimated employing a spatial heteroskedasticity and autocorrelation consistent (HAC) covariance matrix, allowing for both location-specific spatial correlation and cross-sectional spatial correlation. We apply the method developed by Conley (1999) and Hsiang et al. (2011).[11] Note that we use this methodology because it is important to take into account that both shocks and conflicts are clustered in space.[12] We allow for correlation to be over two years for the Newey-West/Bartlett Kernel. In a spatial dimension, we follow Berman and Couttenier (2015), and consider a radius of 100 km for the spatial kernel.

5 Results

Our next task is presenting the estimation results. Firstly, we describe the ones when only the total commodity-price shock is considered as a regressor. Secondly, we disaggregate the total shock in its agricultural, oil and gas, and mining components. Finally, we

[11] We use the STATA routine based on the one from Hsiang et al. (2011), and its extension to multidimensional fixed effects by Fetzer (reg2hdfespatial.ado)

[12] See Appendix B for mines, crops, and oil and gas sub-maps.

perform robustness checks.

5.1 Total shocks

We start by presenting in Table 2 results when in regression (9) the dependent variable is number of incidents and the independent variable $S_{c,t-1}$ equals total shocks, that is, $S^T_{c,t-1}$. Recall that total commodity-price shocks are the sum of agricultural, oil and gas, and mineral prices shocks. We consider different definitions of conflict incidents. Column (1) estimates the model with the broader definition provided by the ACLED database. Column (2) takes UCDP conflict incidents as the dependent variables, which mainly involves armed conflict. Columns (3) and (4) consider ACLED Battles and ACLED Riots and Violence against civilians, respectively. We include cell, country and year fixed effects in all estimations following Berman and Couttenier (2015).

Table 2: Total price shocks and ethnic cleavages. Main results.

VARIABLES	ACLED_incidence	UCDP incidence	ACLED battles	Riots and Violence
	(1)	(2)	(3)	(4)
$ShockTotal(t-1)$	0.050***	-0.009**	0.003	0.046***
	(0.008)	(0.005)	(0.006)	(0.007)
$Excluded_{(t-1)}$	0.020***	0.008***	0.017***	0.013***
	(0.004)	(0.003)	(0.003)	(0.003)
$Monopoly_{(t-1)}$	0.137***	0.039***	0.086***	0.093***
	(0.014)	(0.006)	(0.012)	(0.012)
$ShockTotal(t-1) * excluded_{(t-1)}$	-0.040***	-0.002	-0.007	-0.034***
	(0.008)	(0.005)	(0.006)	(0.008)
$ShockTotal(t-1) * monopoly_{(t-1)}$	-0.116***	-0.013	-0.047***	-0.074***
	(0.020)	(0.009)	(0.015)	(0.017)
$ShockTotal(t-1) * EthnicPol$	-0.059***	-0.008	-0.012	-0.057***
	(0.018)	(0.012)	(0.013)	(0.017)
$ShockTotal(t-1) * EFractional$	0.065**	0.032*	0.030	0.069***
	(0.026)	(0.018)	(0.019)	(0.025)
$DroughtSEPI_{(t-1)}$	-0.007	-0.008	-0.001	-0.002
	(0.010)	(0.006)	(0.007)	(0.009)
$DroughtSEPI_{(t-1)} * excluded_{(t-1)}$	0.016	0.016*	0.008	0.008
	(0.014)	(0.009)	(0.010)	(0.012)
$Mines_{(t-1)}$	0.008	0.012	0.035***	-0.004
	(0.013)	(0.008)	(0.010)	(0.012)
$Mines_{(t-1)} * excluded_{(t-1)}$	0.017	0.008	0.012	0.003
	(0.015)	(0.010)	(0.012)	(0.014)
Observations	174916	174916	174916	174916
R-squared	0.007	0.002	0.004	0.007
CONTROL VARIABLES	YES	YES	YES	YES
CELL FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definitions of ACLED database (ACLED_INCIDENCE, ACLED_BATTLES and RIOTS AND VIOLENCE) and UCDP INCIDENCE. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. p-values are reported in parentheses
*** p<0.01,** p<0.05, * p<0.1

Results suggest that, within cells, the effect of a positive total commodity-price shock on the probability of conflict depends on the definition of conflict employed. In particular, the impact is positive with both ACLED incidences and riots and violence against civilians. However, if we restrict conflicts to the UCDP database – which captures only armed conflict – the impact is negative, supporting the opportunity cost theory. Finally, if we look at ACLED battles, there is no significant impact of a change in commodity prices. These results are consistent with the ones found by McGuirk and Burke (2017), although focusing exclusively on agricultural price changes and without taking into account different sources of ethnic diversity and their interactions with income shocks; that is, we obtain very similar qualitative results in a broader setting. These authors argue that data on battles and/or armed conflict are more related to violence aimed at controlling territories (what they call "factor conflict"), and data on riots, protests and violence against civilians are more associated to smaller-scale conflict over the appropriation of surplus (which they call "output conflict").

We follow Berman et al. (2015 and 2017) to quantify the effect of the variables. In particular, we start from the mean values of the independent variables, and look at the impact of a one-standard-deviation increase, where the standard deviation is the one coming from the observed changes in the variable from one period to the next. According to this criterion, column (1) implies that a one-standard-deviation increase in the total commodity-price shock from its mean translates into an increase in the overall conflict probability of around 12%, from 0.082 to 0.0916; where 0.082 is the mean value of the dependent variable, and 0.0916 is the result of adding to that mean value the product of the standard deviation described before and the estimated coefficient. As regards armed conflict, column (2) implies that a one-standard-deviation increase in the shock translates into a decrease in the probability of conflict of 8.3%, from 0.0265 to 0.0243. Finally, focusing now in column (4), riots and violence against civilians, a one-standard-deviation increase in $S^T_{c,t-1}$ makes the unconditional probability go up from 0.064 to 0.073, around 14%.

The main lesson is that whereas country-level analysis suggests that there is no evidence of a consistent relationship between price shocks and social instability (Bazzi and Blattman, 2014; Janus and Riera-Crichton, 2015; and Giménez-Gómez and Zewdu, 2016), our results show that there is evidence of a relationship between changes in commodity prices and social conflict.

Table 2 also shows results related to the existence of ethnic heterogeneity. It suggests that, regardless of the nature of the instability, the presence of both excluded and monopoly ethnic groups increase the probability of conflict, and the results are highly significant. The magnitude of the coefficients are more than five times larger in the case that a monopoly group is present in the cell than for excluded groups. As with total shocks, the impact is larger in column (1), ACLED incidence, than in column (2), UCPD incidence; in particular, 0.020 versus 0.008 and 0.137 versus 0.039 for excluded and monopoly, respectively. The results suggest that the presence of these groups triggers an inequality treatment by the government or a grievance mechanism between different ethnic groups.

Also interesting are the estimates associated with the politically-relevant ethnic-groups interaction coefficients. Although both excluded and monopoly groups lead to a higher likelihood of conflict, controlling for political power access we find that interaction of total price shocks with excluded and monopolized groups delivers a negative and significant coefficient in the ACLED incident and riots/violence models. The interpretation is that the probability of conflict in cells with settled excluded and/or monopoly groups is significantly less affected by an increase in total commodity prices. The interaction term with monopoly groups is also negative and significant in column (3), ACLED battles.

Quantitatively, an increase equal to one standard deviation from the mean in the interaction term shock*excluded decreases the probability of social conflict in column (1) by 4.9%, and the probability of riots/violence by 7.5% in column (4). In both cases, the probability of conflict is seven percentage points less than in cells without the presence of these groups. For the interaction term with monopoly groups, column (1) implies that a one-standard-deviation increase reduces the probability of ACLED incidence around 7.4%, and column (4) that the probability of riots and violence against civilians decreases around 9%. Now, the probability of violence in both scenarios is around five percentage points less than in cells without the presence of monopoly groups. Finally, focusing on column (3), a one-standard-deviation increase in the shock*monopoly term decreases the likelihood of battles a 4.2%. These results that point to a lower probability of violence suggest the idea that elites invest in support and/or a more powerful security apparatus.

Moving to polarization and fractionalization, Table 2 shows that the signs of their interactions with commodity-price shocks are opposite, negative for polarization and positive for fractionalization. Both of them appear as significant on the specifications with ACLED general conflict in column (1), and riots and violence against civilians in column (4) as dependent variables. On more polarized cells, because of the interaction between ethnic diversity and conflict, a one-standard-deviation increase of the total shock translates into a decrease of the probability of social conflict and riots/violence of around 6% and 8%, respectively. Even though income shocks raise violent events by around 5% in both cases through their direct effect, on more fragmented cells, these income shocks push further up the probability of conflict by 7% in both columns (1) and (4) due to the indirect effect. On these cells, a one-standard-deviation increase in the price shock makes the probability of conflict considerably go up, by 17% and 21% in columns (1) and (4), respectively.

Qualitatively, the interaction with polarization seems to support the opportunity cost or the state capacity channels; that is, in more polarized societies these channels could be stronger. The results coming from the interaction with fractionalization go in the opposite direction and support a higher likelihood of conflict. As we mentioned in section 2, cells with higher levels of fractionalization tend to have also a larger proportion of markets and trade. Thus suggesting lack of monitoring capacity, or in other words, a lower level of institutional quality. Other channels, such as the appropriation of resources or looting could also explain these results. Clearly, we need further studies to find the exact cause of these effects on conflict.

Another message that we can extract from Table 2 is that, once we control for income shocks and ethnic diversity, there is little role left for climatic conditions: droughts are not significant in any column. We can see as well that the mines dummy is not significant either, with the exception of battles – the presence of mines increases their likelihood.[13] Finally,

[13]On Appendix C, we show that the dummy variable mines increases the likelihood both on civil war and battles when there is no interaction term. Nevertheless, these results on mines should be taken with caution because of the possible reverse causation. We try to control for this potential issue following Berman et al. (2017), coding as one only if a mine has been registered as active in the period 1990-2014 after its discovery

we look at results for the two additional interactions that relate the variable excluded groups with the variables mines and droughts; we see that there is no clear evidence to support a significant role in social conflict.

The following should go as a footnote at the end of the paragraph before last. "Comparing to previous literature, at the country level, Janus and Riera-Crichton (2015) and Gimenez-Gomez and Zewdu (2016) find that adverse changes in prices increase the probability of political instability in countries with higher level of ethnic polarization, whereas ethnic fractionalization has a mixed impact. In contrast, we we find that both variables have a well defined effect for all definitions of violence.

5.2 Disaggregated shocks

In order to further evaluate the impact of income shocks and social cleavages on conflict, we estimate regression (9) but now disaggregating the total commodity-price shocks into its agricultural, oil and gas, and mineral components; that is, we consider that the vector $S_{c,t-1}$ equals $S^{A}_{c,t-1}$, $S^{E}_{c,t-1}$, $S^{M}_{c,t-1}$. We focus on validating that the probability of conflict is heterogeneous across cells when there are different types of commodity shocks and ethnic cleavages.

Table 3 presents the results with the ACLED incidence as the dependent variable. Tables 4 and 5 replicate the model (9) for each of the additional dependent variables: the UCDP incidence, the ACLED battles and the riots and violence against civilians. Recall that a UCDP incident is more restrictive than a ACLED incident, because a UCDP incident requires at least 1 fatality on the event, and involves only organized armed groups that have fought in battles that directly caused at least 25 fatalities over all the period of the dataset. We present results introducing the disaggregated shocks one at a time – columns (1) to (3) in Tables 3 and 4, and columns (1) to (3) and (5) to (7) in Table 5 – and also incorporating all of them at the same time – column (4) in Tables 3 and 4 and columns (4) and (8) in Table 5.

Let us focus first on the estimated impact of income shocks, in Table 3 (ACLED incidence) we find that the estimated coefficients associated with the agricultural and mineral shocks are positive and strongly statistically significant. As mentioned previously, these results for agricultural price shocks are consistent with McGuirk and Burke (2017). The sign and significance of mineral commodity shocks are, in turn, consistent with results found by Berman et al. (2017). Nevertheless, we notice that these authors analyze changes in price levels, instead of our arguably more exogenous price shocks. Quantitatively, looking at column (4), a one-standard-deviation increase in either agricultural or mineral shocks from their means translate into an approximate increase of the probability of social conflict from 0.082 to 0.089, that is, around 8.4%. These positive estimated effects suggest that, in a broader perspective of conflict, the main mechanisms associated which linking the variation of the commodity prices and conflict could be through of looting and a weak state capacity.

or known production. Berman et al. find that mines are statistically significant in every case, whereas for us, they are significant with civil war or battles. Their results can differ from ours because they use a higher quality, private database called The Raw Material Data, Intierra RMG, to which we do not have access. Other recent papers such as Adhvaryu et al. (2017) do employ the data set that we use.

Table 3: The effect of commodity prices on conflicts and political and ethnic diversity. ACLED incidence. Main results

VARIABLES	ACLED_incidence (1)	ACLED_incidence (2)	ACLED_incidence (3)	ACLED_incidence (4)
$ShockAg_{(t-1)}$	0.044***			0.041***
	(0.009)			(0.009)
$ShockExt_{(t-1)}$		0.021		0.018
		(0.015)		(0.015)
$ShockMineral_{(t-1)}$			0.141***	0.133***
			(0.033)	(0.033)
$Excluded_{(t-1)}$	0.020***	0.021***	0.020***	0.020***
	(0.004)	(0.004)	(0.004)	(0.004)
$Monopoly_{(t-1)}$	0.125***	0.146***	0.145***	0.125***
	(0.014)	(0.015)	(0.015)	(0.014)
$ShockAg_{(t-1)} * excluded_{(t-1)}$	-0.035***			-0.032***
	(0.009)			(0.009)
$ShockExt_{(t-1)} * excluded_{(t-1)}$		-0.041**		-0.037**
		(0.019)		(0.019)
$ShockMineral_{(t-1)} * excluded_{(t-1)}$			-0.075*	-0.072*
			(0.042)	(0.042)
$ShockAg_{(t-1)} * monopoly_{(t-1)}$	-0.234***			-0.231***
	(0.040)			(0.039)
$ShockExt_{(t-1)} * monopoly_{(t-1)}$		-0.043*		-0.027
		(0.023)		(0.023)
$ShockMineral_{(t-1)} * monopoly_{(t-1)}$			-0.043	-0.074
			(0.172)	(0.178)
$ShockAg_{(t-1)} * EthnicPol$	-0.061***			-0.062***
	(0.022)			(0.022)
$ShockExt_{(t-1)} * EthnicPol$		0.032		0.030
		(0.037)		(0.037)
$ShockMineral_{(t-1)} * EthnicPol$			-0.289**	-0.299**
			(0.132)	(0.133)
$ShockAg_{(t-1)} * EFractional$	0.068**			0.073**
	(0.033)			(0.033)
$ShockExt_{(t-1)} * EFractional$		0.019		0.025
		(0.034)		(0.034)
$ShockMineral_{(t-1)} * EFractional$			0.299	0.327
			(0.219)	(0.222)
$DroughtSEPI_{(t-1)}$	-0.005	-0.009	-0.008	-0.005
	(0.010)	(0.010)	(0.010)	(0.010)
$DroughtSEPI_{(t-1)} * excluded_{(t-1)}$	0.014	0.016	0.015	0.014
	(0.014)	(0.014)	(0.014)	(0.014)
$Mines_{(t-1)}$	0.008	0.006	0.005	0.007
	(0.013)	(0.013)	(0.013)	(0.013)
$Mines_{(t-1)} * excluded_{(t-1)}$	0.016	0.018	0.020	0.018
	(0.015)	(0.015)	(0.015)	(0.015)
Observations	167368	167368	167368	167368
R-squared	0.007	0.006	0.007	0.007

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of ACLED incidence database (ACLED_INCIDENCE). LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. Cell, country and year fixed effects. Control variables are included. p-values are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 4: The effect of commodity prices on conflicts and political and ethnic diversity. UCDP incidence. Main results

VARIABLES	UCDP incidence (1)	UCDP incidence (2)	UCDP incidence (3)	UCDP incidence (4)
$ShockAg_{(t-1)}$	-0.014**			-0.013**
	(0.005)			(0.005)
$ShockExt_{(t-1)}$		-0.019		-0.019*
		(0.012)		(0.012)
$ShockMineral_{(t-1)}$			-0.008	-0.007
			(0.013)	(0.013)
$Excluded_{(t-1)}$	0.005**	0.006***	0.006**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
$Monopoly_{(t-1)}$	0.028***	0.033***	0.032***	0.027***
	(0.004)	(0.005)	(0.005)	(0.004)
$ShockAg_{(t-1)} * excluded_{(t-1)}$	0.003			0.003
	(0.006)			(0.006)
$ShockExt_{(t-1)} * excluded_{(t-1)}$		-0.002		-0.002
		(0.013)		(0.013)
$ShockMineral_{(t-1)} * excluded_{(t-1)}$			-0.017	-0.017
			(0.023)	(0.023)
$ShockAg_{(t-1)} * monopoly_{(t-1)}$	-0.098***			-0.099***
	(0.018)			(0.018)
$ShockExt_{(t-1)} * monopoly_{(t-1)}$		0.027**		0.024**
		(0.012)		(0.012)
$ShockMineral_{(t-1)} * monopoly_{(t-1)}$			-0.536	-0.533
			(0.358)	(0.358)
$ShockAg_{(t-1)} * EthnicPol$	-0.012			-0.012
	(0.013)			(0.013)
$ShockExt_{(t-1)} * EthnicPol$		0.009		0.009
		(0.029)		(0.029)
$ShockMineral_{(t-1)} * EthnicPol$			-0.053	-0.060
			(0.069)	(0.069)
$ShockAg_{(t-1)} * EFractional$	0.036**			0.037**
	(0.018)			(0.018)
$ShockExt_{(t-1)} * EFractional$		0.025		0.025
		(0.021)		(0.021)
$ShockMineral_{(t-1)} * EFractional$			0.073	0.083
			(0.095)	(0.095)
$DroughtSEPI_{(t-1)}$	-0.010*	-0.010*	-0.011*	-0.010*
	(0.006)	(0.006)	(0.006)	(0.006)
$DroughtSEPI_{(t-1)} * excluded_{(t-1)}$	0.023**	0.024***	0.024***	0.023***
	(0.009)	(0.009)	(0.009)	(0.009)
$Mines_{(t-1)}$	0.015**	0.016**	0.017**	0.016**
	(0.008)	(0.008)	(0.008)	(0.008)
$Mines_{(t-1)} * excluded_{(t-1)}$	0.011	0.010	0.009	0.010
	(0.009)	(0.009)	(0.009)	(0.009)
Observations	196942	196942	196942	196942
R-squared	0.002	0.001	0.002	0.002

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of UCDP database (UCDP INCIDENCE). LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. Cell, country and year fixed effects. Control variables are included. p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: The effect of commodity prices on conflicts and political and ethnic diversity. ACLED battles conflict and Riots and Violence against civilians. Main results

VARIABLES	ACLED battles (1)	ACLED battles (2)	ACLED battles (3)	ACLED battles (4)	Riots and Violence (5)	Riots and Violence (6)	Riots and Violence (7)	Riots and Violence (8)
$ShockAg_{(t-1)}$	0.001			0.001	0.046***			0.043***
	(0.007)			(0.007)	(0.009)			(0.009)
$ShockExt_{(t-1)}$		0.006		0.004		0.005		0.004
		(0.013)		(0.013)		(0.013)		(0.013)
$ShockMineral_{(t-1)}$			-0.018	-0.019			0.150***	0.143***
			(0.019)	(0.019)			(0.031)	(0.031)
$Excluded_{(t-1)}$	0.017***	0.017***	0.017***	0.017***	0.013***	0.013***	0.013***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$Monopoly_{(t-1)}$	0.073***	0.089***	0.089***	0.073***	0.088***	0.098***	0.097***	0.088***
	(0.011)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
$ShockAg_{(t-1)} * excluded_{(t-1)}$	-0.005			-0.005	-0.027***			-0.024***
	(0.007)			(0.007)	(0.008)			(0.008)
$ShockExt_{(t-1)} * excluded_{(t-1)}$		-0.018		-0.017		-0.038**		-0.035**
		(0.017)		(0.017)		(0.018)		(0.018)
$ShockMineral_{(t-1)} * excluded_{(t-1)}$			0.008	0.007			-0.085**	-0.082**
			(0.032)	(0.032)			(0.040)	(0.040)
$ShockAg_{(t-1)} * monopoly_{(t-1)}$	-0.173***			-0.176***	-0.116***			-0.114***
	(0.030)			(0.030)	(0.035)			(0.035)
$ShockExt_{(t-1)} * monopoly_{(t-1)}$		0.011		0.022		-0.022		-0.014
		(0.017)		(0.017)		(0.021)		(0.022)
$ShockMineral_{(t-1)} * monopoly_{(t-1)}$			0.055	0.056			-0.198	-0.225
			(0.259)	(0.263)			(0.207)	(0.211)
$ShockAg_{(t-1)} * EthnicPol$	-0.016			-0.016	-0.056***			-0.057***
	(0.016)			(0.016)	(0.021)			(0.020)
$ShockExt_{(t-1)} * EthnicPol$		0.030		0.030		0.011		0.008
		(0.032)		(0.032)		(0.036)		(0.036)
$ShockMineral_{(t-1)} * EthnicPol$			0.076	0.066			-0.343**	-0.347**
			(0.066)	(0.066)			(0.137)	(0.138)
$ShockAg_{(t-1)} * EFractional$	0.034			0.034	0.063**			0.068**
	(0.024)			(0.024)	(0.031)			(0.031)
$ShockExt_{(t-1)} * EFractional$		0.032		0.032		0.042		0.048
		(0.023)		(0.023)		(0.034)		(0.033)
$ShockMineral_{(t-1)} * EFractional$			-0.112	-0.097			0.384*	0.401*
			(0.091)	(0.091)			(0.229)	(0.230)
$DroughtSEPI_{(t-1)}$	0.001	-0.001	-0.001	0.001	-0.001	-0.004	-0.003	-0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)
$DroughtSEPI_{(t-1)} * excluded_{(t-1)}$	0.006	0.007	0.008	0.006	0.008	0.008	0.008	0.008
	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)	(0.012)	(0.012)
$Mines_{(t-1)}$	0.035***	0.035***	0.035***	0.035***	-0.003	-0.005	-0.006	-0.005
	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)	(0.012)	(0.012)
$Mines_{(t-1)} * excluded_{(t-1)}$	0.013	0.013	0.013	0.012	0.002	0.004	0.006	0.005
	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	167368	167368	167368	167368	167368	167368	167368	167368
R-squared	0.004	0.004	0.004	0.004	0.007	0.006	0.007	0.007

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of ACLED battles database (ACLED_BATTLES and RIOTS AND VIOLENCE). LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. Cell, country and year fixed effects. Control variables are included. p-values are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

In Table 4 (UCDP incidence), agricultural price shocks are negatively and statistically significant at the 1%, supporting the opportunity cost theory. As mentioned previously, this result is consistent with previous literature. Quantitatively, column (4) implies that an increase of a one-standard-deviation decreases the probability of armed conflict by 7.7%. Surprising, column (4) says that an increase in oil and gas commodity shock leads to decrease conflicts that involve battles in the UCDP context. However, this coefficient is only significant at 10%. In Table 5 (ACLED battles and riots/violence), in turn, we find no relationship between short-time price variations and the likelihood of battles, but a strongly positive one between both agricultural and mineral shocks and the probability of riots and violence against civilians. To gauge the magnitude, consider again the specification in column (8), a one-standard-deviation increase in either the agricultural or the mineral price shocks from its mean increases the probability of riots and violence against civilians from 0.064 to 0.071, nearly 11%. These results support the theories that a sharp rise in food prices leads accelerated protests because of a reduction in household income. An example, it was the protest during the Arab spring motivated, at least in part, because of the sharp rise of basic agricultural prices.

Next, we look at results related to the politically relevant ethnic groups interactions. Tables 3 to 5 show that the effect of rising commodity prices on the probability of both general social conflict and social unrest is heterogeneous across cells. Specifically, the coefficients on the interaction between the agricultural shock and excluded groups are negative and significant in Tables 3 and 5. Columns (4) and (8) in Tables 3 and 5, respectively, imply that a one-standard-deviation increase in the agricultural price shock delivers a decline in the probability of both ACLED incidence and riots/violence of about 4% if excluded groups are present. We find the same result qualitative results for the interaction between both mineral and oil/gas price shocks and excluded groups. Quantitatively, increasing mineral prices translates into a reduction in the increase of violence of about 2% (Table 3, column (4)) and by -3% (Table 5, column 8) when excluded groups are located within the cell. These numbers are smaller in the case of oil and gas: -0.7% and 2%, respectively. These results support Berman and Couttenier (2015)'s idea of remoteness explained before.

Regarding interaction of monopoly groups and commodity shocks, we find a negative and statistically significant relationship in the case of agriculture, independently of the definition of conflict, being the impact on the probability of both armed conflict and battles larger than on social unrest. These conclusions again support a stronger state capacity mechanism within these cells. More specifically, tables 3 (column (4)) and 5 (columns (4) and (8)) say that a one-standard-deviation increase in the agricultural price shock from its mean generates a decline of 3.5% in the probability of ACLED incidence, of 4,4% in the likelihood of riots and violence against civilians and 9% in the case of battles in cells with monopoly groups settlements. In Table 4, column (4), this impact on the armed-conflict probability decreases from 0.027 to 0.022, a 8% fall. compared to cells without monopoly groups, whereas in Table 5, column (4), the battles probability decreases from 0.041 to 0.037, nearly 9%.

Interestingly, Table (4) also shows a positive, statistical-significant link between oil/gas price shocks within monopoly-groups cells and armed conflict (UCDP incidence). This finding can be interpreted as opposite to the conclusions in Basedau and Pierskalla (2014). Notice, however, that we analyze short-term variations in prices, whereas Basedau and Pierskalla study the presence of an oil and gas stock in cells. A plausible interpretation is the existence of a rapacity mechanism in these areas (Dube and Vargas, 2013): the feasibility of a rebellion against the central power by fighting groups with ethnic political grievances increases with the potential gains from the appropriation of natural resources rents. Qualitatively, taking baseline probabilities and the specification model in column (4) of Table 4, a one-standard-deviation increase in the oil/gas price shock from its mean makes the armed-conflict probability rise a 3% more in cells with monopoly groups.

Results related to spatial ethnic diversity are also revealing. The coefficients on the interaction between ethnic polarization and agricultural and mineral price shocks show no significance to explain the probability of armed conflict and battles, but are always negative and significant in the regressions for ACLED incidents and riots/violence, thus helping to mitigate the direct effect of income shocks on social conflict. For example, a one-standard-deviation increase in the agricultural prices shock rises, on average, ACLED incidence (Table 3, column (4)) from 0.082 to 0.0834, but the impact is a 6% larger in cells where ethnic polarization equals zero. The same type of shock affects the probability of riots and violence against civilians (Table 5, column (8)) a 7% more (from 0.064 to 0.0662) in zero-polarized cells. Concerning mineral price shocks, the probability of ACLED incidence and riots/violence increases by 2% and 3%, respectively; however, the interaction with ethnic polarization implies that the impact is 10% and 15% higher, respectively, in cells without any ethnic polarization. Interaction between oil/gas shocks and ethnic polarization show no significance in all cases.

Finally, we also look at the interactions between commodity price shocks and ethnic fractionalization. In Tables 3 to 5, we find that these interactions are both significant and positive for agricultural shocks, with the exception of ACLED battles. To gauge the magnitudes, in Table 3, column (4), a one-standard-deviation increase in the agricultural shock increases ACLED incidence by 13%, this effect is a 5% higher when we include interactions. Moreover (Table 4, column(4)), the probability of armed conflict increases by 1%, which implies a reversion in the direct negative impact of agricultural shocks of nearly 9%. Finally, for the same type of shock, the probability of riots and violence against civilians increases by 15%, a 4% less in cells without interaction.

5.3 Robustness analysis

In this section, we carry out several robustness checks. In particular, we start considering the following modifications of the basic regression specifications. Firstly (Tables C1 to C7), we present results without ethnic-diversity interaction terms. Secondly (Tables C8 to C10), we add country-specific time trends, because within-country trends in conflict events might be correlated to temporal trends in the global demand for food or to world commodity prices. Thirdly (Table C11), we employ the definition of price shocks developed by Fdjelde (2015), which proxies them by directly calculating the change in prices between two consecutive years, and therefore, should suffer more from endogeneity issues. Fourthly (Table C12), a cell-specific control variable that takes a climate indicator measured in the cell-specific growing season of a crop is introduced; this variable is associated to high climate variability, and hence, could influence the cell's agricultural production. Fifthly (Table C16), a grid panel with cells of 110 x 110 km is considered. Additionally, we also present standard errors with alternative spatial and temporal kernels in the computation in Table C17. Finally (Table C18), commodity shocks on neighboring cells are introduced in the regression. We find that our results for the effect of income shocks are fully robust, and in many cases, also the ones related ethic-diversity interactions. In particular, the latter terms lose more often their significance when country-specific time trends are introduced and when shocks are proxied using year-to-year changes. In sum, we conclude that results are quite robust to the above alterations.

Remarkably, our robustness test with the climate indicator in the cell-specific growing season of a crop, and its interaction with the excluded group are again significant for armed conflict, and for the ACLED Incidence and Riots, respectively. These results suggest that loss of pasture or climate-induced crop failure should also indicate hunger and dramatic loss of income.

Next, following McGuirk and Burke (2017), we perform a robustness test that concerns the dependent variable riots and violence against civilians. The reason is that our main results predict that an increase of either agricultural or mineral prices leads to a higher level of riots and violence. Berman et al. (2017) find the same result for mines, suggesting that indeed riots/violence are probably spatially concentrated around mine locations. As regards agricultural shocks, work by McGuirk and Burke (2017) and Bellemare (2015) implies that higher food prices can cause more food riots. These food riots, usually driven by a desire to either appropriate from others (Hendrix and Haggard, 2015) or incite government policy changes in favor of consumers in a food price crisis (Bellemare, 2015), tend to take place in urban areas, as pointed out by McGuirk and Burke (2017). Hence, we interact the lag of our shock indexes with urban areas.[14] Results from this exercise are presented in Table C13. The new interaction terms show up as strongly significant although with different signs. The conclusion is that agricultural and mineral price shocks are more likely to trigger conflict in urban and rural areas, respectively.

Our last robustness check employs two alternative dependent variables: the onset and offset of conflict events. According to Beck and Katz (2011), estimated coefficients can be biased when using incidence if lags of the dependent variable are not included as additional regressors. This criticism does not really apply to our approach, because incidents are not highly persistent at the cell level. Nevertheless, we look at the impact on onsets and offsets in order to check robustness. Tables C14 and C15 present the results for total and disaggregated shocks, respectively. We can see that results are very robust for the case of conflict onset. For conflict offset, we find that the coefficients are usually not statistically significant, with the exception of the interaction terms of mines and droughts with excluded groups; note however that the results for conflict offset are less reliable because of the much smaller sample size.

6 Conclusions

Barrett (2003, pg. 11) argues *"..food insecurity and sociopolitical instability..[..], not only affect one another, they also share so many common drivers that it becomes impractical to identity causal mechanisms with statistical rigor [...]"*.

This paper has studied how different types of commodity shocks across ethnically-

[14]The numbers for urban areas are provided by PRIO-GRID 2.0 from the ISAM-HYDE land use dataset. They provide the percentage of urban area in each cell.

diverse cells affect several definitions of social conflict outcomes, and hence, food security. To that end, information on the location of conflict and social unrest for the entire African continent has been used, employing a fine-grained panel data for the period 1997-2014 with a spatial resolution of 0.5 x 0.5 degree latitude and longitude. We have contributed to the existing literature in several ways. Firstly, we have created exogenous commodity-price shocks within cells. More specifically, we have constructed these shocks using the non-predictable component of price changes delivered by the regression of the logarithm of prices on their lagged values and a time trend. Secondly, our work has jointly considered several types of ethnic diversity and conflict measures that have been employed separately in the literature. Finally, we have searched for the direct effect of income shocks as well as indirect channels that might work through ethnic diversity. The goal has been to give a more complete vision of the determinants of violence than previous literature.

We have obtained multiple interesting results that identify the heterogeneous impact of income shocks across conflict definitions and ethnic diversity measures. In particular, we have found that positive agricultural and mineral price shocks increase the probability of social conflict, riots, and violence across civilians in general, but decrease the incidence of armed conflict. Oil and gas price shocks, on the other hand, do not show significant direct effects. In addition, the presence of extreme cases of ethnic-group political status, what we have called excluded and monopoly groups, implies a higher level of violence independently of the conflict definition. Searching for the interaction channel between income shocks and ethnic diversity, our results imply that the existence of excluded groups, monopoly groups, or more polarized societies tend to reduce the positive impact of income shocks on the probability of conflict, whereas ethnic fractionalization always raises it. We have also found that, even after controlling for agricultural-income shocks, droughts have a negative weakly significant effect on armed conflict, and as previous literature, a strong positive effect of their interaction with excluded groups on the likelihood of armed conflict

We argue that these results imply that the relevance of each theory depends on the type of conflict and cell's ethnic characteristics. The direct effect of commodity-price shocks on armed conflict is driven mainly by the opportunity cost of going to a war, whereas the one of riots and violence against civilians is more related to the state-is-prize theory. The latter seems to suggest that riots and social conflict are mainly driven by a desire to increase the levels of income redistribution in the society. In turn, the significant interaction terms between income shocks and either ethnic polarization or political discrimination suggest also a role for state capacity to meliorate violence.

Our findings point out different avenues for future research. From a policy side, the results could be interpreted as demanding an agricultural price-stabilization mechanism, if high price fluctuations lead to higher levels of violence. Whether this is the case and the right type of policy depending on the nature of ethnic diversity deserves further investigation. There are also several factors that can be behind the income-shock indirect-effect channeled through ethnic diversity, and that we have pointed out in the text: trust, monitoring costs, labor market frictions, and quality of institutions. Incorporating these aspects into the analyses can represent as well a promising source of future research.

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Reexamining the Role of Income Shocks and Ethnic Cleavages on Social Conflict in Africa at the Cell level.

—–Appendix A. Data Definitions—–

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Data description and sources

1.1.1 Structure of the Dataset. Our baseline unit of analysis is a full grid of Africa divided into sub-national units of 0.5 x 0.5 grades latitude and longitude (which corresponds to a cell of roughly 55 x 55 kilometers at the equator). This is the result of intersecting grid cells provided by the PRIO-GRID[1] structure, with a map of the entire Africa and their national political borders provided by The Global Administrative Unit Layers (2010), a project from UN Food and Agricultural Organization (FAO). The use of the PRIO-GRID allows us to easily include cell specific data from this dataset. All conflict events are aggregate at the level of the cell. Administrative boundaries are taken at the end of our sample period. The country which stands for the largest share of a cell's area is assigned to this cell.

1.1.2 Conflict Events. We make use of two different datasets containing the geo-location of conflict events in Africa: **the UCDP-Georeferenced Event dataset (UCDP-GEO)**, version 5.0 (Croicu and Sundberg, 2016), and **the Armed Conflict Location and Event Dataset (ACLED Dataset)** (Raleigh et al., 2017). These data cover different countries and time period. These events are collected from various sources, including ones from humanitarian agents, research publications, or local, regional or international press news. The use of the different dataset provides us to test both different competitive theories and the robustness of our results. In each dataset the unit of observation is the event. They contain information of the latitude and longitude, and the precise day (in the most cases) of conflict events. UCDP defines an event as : "An incident where armed force was used by an organised actor against another organized actor, or against civilians, resulting in **at least 1 direct death at a specific location and a specific date**Ó. In addition: "Only events linkable to a UCDP/PRIO Armed Conflict, a UCDP Non-State Conflict or a UCDP One-Sided Violence instance are included. Events are included for the entire period, i.e. both for the years when such conflicts were active (years that have crossed the 25

[1] http://www.prio.no/Data/PRIO-GRID/

battle related deaths threshold) and for the years when such conflicts where not active (the remainder). The dataset includes all three types of UCDP organised violence: state-based conflict, non-state conflict and one-sided violence".

Meanwhile, ACLED Dataset registers **"a range of violent and non-violent actions by political agents, including governments, rebels, militias, communal groups, political parties, rioters, protesters and civilians"**. In a broader perspective, ACLED records violent activity both within and outside the context of a civil war. To that end, there is not specifically a battle-related deaths threshold.

In any case, the difference between these dataset allows as to study both robustness checks and a broader perspective of the conflict issue, in particular the diffusion of the violence in space and over time. (Bernan, Coutteneir, Rohner and Thoering, 2017).

Specifically, our dependent variables could be:

- **UCDP Incidence**: We aggregate to the cell-year level, coding the variable as one if any conflict from UCDP data took place, zero otherwise.
- **ACLED Incidence**: We aggregate to the cell-year level, coding the variable as one, if any conflict from ACLED data took place, zero otherwise.
- **ACLED battles**: We aggregate to the cell-year level, coding the variable as one, if conflicts from ACLED data took place defined as: "Battle-No change of territory", "Battle-Non-state actor overtakes territory" and "Battle-Government regains territory", zero otherwise.
- **Riots and Violence against civilians**: We aggregate to the cell-year level, coding the variable as one, if conflicts from ACLED data took place defined as: "Riots/Protests" and "Violence against civilians", zero otherwise.

1.1.3 Crop cover data. We use the crop production share in each cell. Data on the geographical production of agricultural crops is drawn from the M3-Crops data by Monfreda et al, 2008[2]. Total production is the production crop in metric tons of land area mass of a grid cell. We aggregate the raster information for production at

[2]http://www.earthstat.org/data-download/

the 5 arc minutes x 5 arc minutes resolution (about 9.2 km x 9.2 km at the equator), at the resolution of our grid structure. Thus, we match the crops maps raster with our grid structure, taking the statistical medium value of each crop on each cell.

1.1.4 Natural resources: To each cell-year, we merge information of Natural Resources from PRIO-GRID v.1.2 and v.2.0 datasets with USGS dataset from mines. Specifically:

- **Petrol (YES=1)**. Source: PRIO-GRID v.1.2 It is a dummy variable for whether onshore petroleum deposits have been found within the given grid cell for any given year, based on the Petroleum Dataset v.1.2. We merge petrolium deposites with our full grid of Africa.
- **GAS (YES=1)**. Source: PRIO-GRID v.1.2 It is a dummy variable for whether onshore gas deposits have been found within the given grid cell for any given year, based on the Petroleum Dataset v.1.2. We merge petrolium deposites with our full grid of Africa.
- **OILGAS (YES=1)**. Source: PRIO-GRID v.1.2 It is a dummy variable for whether jointly onshore petroleum and gas deposits have been found within the given grid cell for any given year, based on the Petroleum Dataset v.1.2. We merge petrolium deposites with our full grid of Africa.
- **MINES (YES=1)**. This dummy accounts any presence of gold, diamond and gem mines from the variables: diamsec-y ,diamprim-y, gem-y, goldplacer-y, goldvein-y, and goldsurface-y, in the PRIO-GRID v.2.0 dataset. We have information about active diamond or gem mines before 2006. In addition, we add the presence of mines from the USGS data. It covers the presence of several types of mineral for active mines until 2003. In fact, to avoid endogeneity concerns, we define mines=1 in cells where at least a mine has been registered as active in the period (1990-2014) after its discovery or known production.

1.1.5 Ethnicity

- **Political Status**:
  - **Exclusion (Excluded)**. It is a dummy variable for whether a excluded group is settled in the grid cell for the given year. This variable is derived from the excluded groups variable, that is provided in PRIO-GRID v.2.o and derived from the GeoEPR/EPR 2014 update 2 dataset. Excluded variable "counts the number of excluded groups (discriminated or powerless)". In fact, powerless means "that elite representatives hold no political power at either national or the regional level without being explicitly discriminated against". On the other hand, discriminated means "that group members are subjected to active, intentional, and targeted discrimination, with the intent of excluding them from both regional and national power. Such active discrimination can be either formal or informal".(Cederman, Wimmer and Min, 2010).
  - **Monopoly (Monopoly)** It is a dummy variable for whether a monopoly group is settled in the grid cell for the given year. This variable is built matching the settlement areas from Ethnic Power Relations (EPR) Dataset Core 2014 with the grid structure provided in PRIO-GRID v.2.0. Monopoly means "that elite members hold monopoly power in the executive to the exclusion of members other ethnic groups". (Cederman, Wimmer and Min, 2010).
- **Spatial Ethnic Diversity**: Following Montalvo and Reynal-Querol, (forthcoming), we use data form Geo-referencing of Ethnic Groups (GREG) (Weimar, Rod and Cederman, 2010), which provides the geospatial location of ethnic groups as polygons. As Montalvo and Reynal Querol, by intersecting our grid structure and groups territories , we are able to estimate the share of area within each cell by groups. For each grid cell we construct two diversity type of measures of ethnic diversity: Ethnic Fractionalization and Ethnic Polarization.

– **Spatial Ethnic Fractionalization** The Spatial Ethnic Fractionalization index is based on the standard Herfindahl-Hirschman index of ethnic diversity or fractionalization.

$$\mathrm{EF}_c = 1 - \sum_{i=1}^{N} \pi_i^2 = \sum_{i=1}^{N} \pi_i (1 - \pi_i) \tag{1}$$

where π is the proportion of area who belong to ethnic group i (For i=1,......,N).

– **Spatial Ethnic Polarization** We compute the spatial index of polarization measure which Montalvo and Reynal-Querol (2005) construct adapted from Esteban and Ray (1994).

$$\mathrm{EP}_c = 4 \sum_{i=1}^{N} \pi_i^2 (1 - \pi_i) \tag{2}$$

where π is the proportion of area who belong to ethnic group i (For i=1,......,N).

1.1.6 Specific-cell variables We merge our data with the PRIO-GRID v.2.0 dataset (Tolefsen, Strand and Buhaug, 2012) [3] which contains a number of additional cell specific variables that we use both in our baseline model and in our robustness analysis. These include in particular information on GDP and population (included in prio-grid but originally from G-econ), the night light calibration mean in a cell as a proxy of the gross cell product, climate (temperature, rainfall and droughts), as well as distances between the cellÕs centroid and international borders and to the capital city. Description of the additional variables:

Log of Night lights per capita. To build a proxy of the level of development for each cell, we estimate the variable income per-capita from 1992 to 2012. Firstly, we use the variable "night light calibration mean" from the PRIO-GRID 2.0: This variable "measures nighttime light emission from the DMSP-OLS Nighttime Lights Time Series Version 4), calibrated to account for intersatelite differences and interannual sensor decay using calibration values from Elvidge et.al. (2013). Values are standardized to be between 0 and 1, where 1 is the highest observed value in the time-series, and 0 is the lowest ". Secondly, we use the variable "pop hyd sum", taken again from PRIO-GRID v.2.0, which "measures the sum of number of persons within each cell"

[3]http://grid.prio.org)

(History Database of the Global Environment (HYDE) version 3.1). Population estimated are available each five years and we interpolate values between data. Finally, once we estimate the total nightlight mean and population per cell, we estimate the proxy of GDP per capita as follows:

$$\text{Ln}(\text{NL}_{ct})=\ln\left(\frac{0.1+nightlight_{ct}}{0.1+population_{ct}}\right) \tag{3}$$

Log of population. Log of total cell population (pop hyd sum interpolate). Source: HYDE Dataset (from PRIO-GRID 2.0).

Population density (Denpob). Source: Socioeconomic Data and Applications Center (sedac) NASA-Columbia University. We use the Gridded Population of the World (GPWFE), which is based on national census and satellite images. GPWFE provides information on human population at 2.5 arc-minutes resolution for 1990, 1995, 2000, 2005, 2010 and 2015 (projected). We merge the raster data with our grid structure calculating the average population by cell. Finally, we interpolate the data in order to create a cell-year variable. We also calculate a robustness variable of population with this data.

Climate variables.

- **Drought SEPI**: "droughtyr-speigdm gives the proportion of months out of 12 months that are part of the longest streak of consecutive months ending in the given year with SPEI-1 values below -1.5. For a year where the longest consecutive streak of months below -1.5 is three, the cell will be given a value of 3/12 = 0.25. When the longest streak starts in the previous year, it is only counted and included in the year in which the streak ended. Theoretically, the proportion can become higher than 1". From PRIO-GRID v.2.0 dataset. Original source: SPEI Global Drought Monitor.

- **Crop Drought**: "droughtcrop-speigdm gives the proportion of months in the growing season that are part of the longest streak of consecutive months in that growing season with SPI1 values below -1.5. The growing season is the growing season for the cellÕs main crop, defined in the MIRCA2000 dataset v.1.1. For growing seasons that cross 1 January, we define the whole season to belong to the year in which the season ended. Thus, a year with two consecutive months below -1.5 during the growing season that started in September the previous year and ended in March in the current year, is given a value of $2/8 = 0.25$. Each year only have defined one growing season. Original source Standardized Precipitation and Evapotranspiration Index SPEI-1 from the SPEI Global Drought Monitor.

- **DISTANCES**
  - **Distance to nearest contiguous country (Lnbdist1)**: Log of bdist1 Source: PRIO-GRID v.2.0. Log of the distance to nearest contiguous country (bdist1). "This variable gives the spherical distance in km from the cell centroid to the border of the nearest land-contiguous neighboring country, based on country border data using cShapes v.0.4-2".
  - **Distance to capital (Lncapdist)**: Log of capdist Source: PRIO-GRID v.2.0. Log of the distance to the national capital city (capdist1). "This variable gives the spherical distance in km from the cell centroid to the national capital city in the corresponding country, based on coordinate pairs of capital cities derived from the cShapes dataset v.0.4-2. It captures changes over time wherever relevant.

The following data and their definition are given from the PRIO-GRID v.2.0.

- **LANDUSE VARIABLES**.
  - **urban**: Source: PRIO-GRID v. 2.0 .This variable "gives the percentage area of the cell covered by urban area, based on ISAM-HYDE land use data. To measure the coverage of urban areas the dataset includes the percentage urban areas in a cell extracted from the ISAM-HYDE historical land use dataset. To compute urban-ih its follows the land cover classification system

used by ISAM-HYDE and its aggregates to the category "Urban" (land use class "Urban"). In PRIO-GRID, this indicator is available for the years 1950, 1960, 1970, 1980, 1990, 2000, and 2010". We use this variable interpolated.

Reexamining the Role of Income Shocks and Ethnic Cleavages on Social Conflict in Africa at the Cell level.

—–Appendix B: Maps—–

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1 Appendix 2. Maps

1.1 Grid cells Africa

Figure 1: Cells Africa

1.2 Ethnic Africa

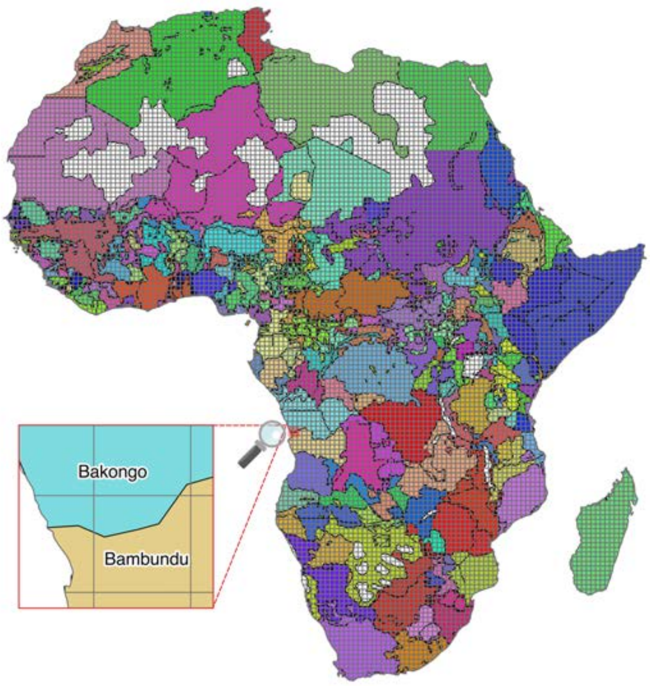


Figure 2: Ethnias

1.3 Political Ethnic diversity

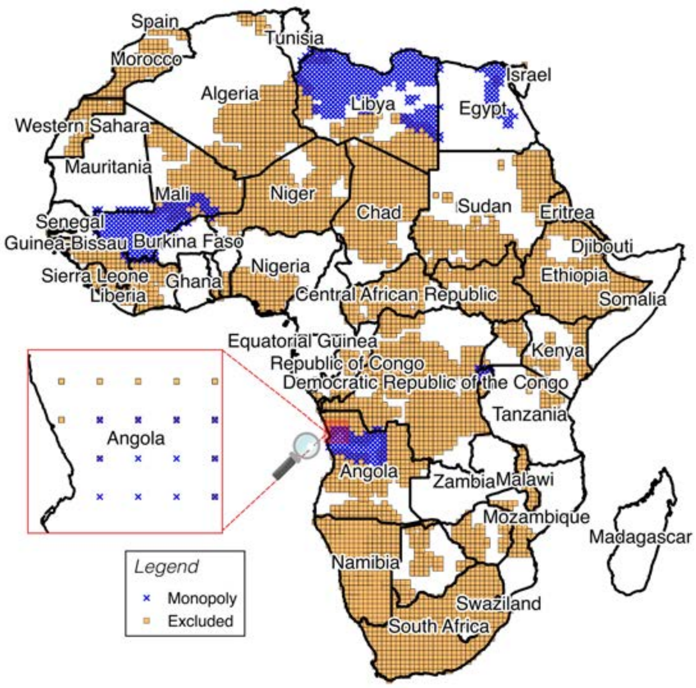
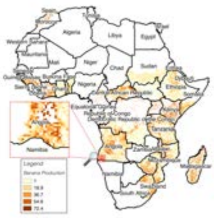
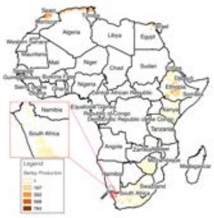


Figure 3: Excluded and monopoly groups

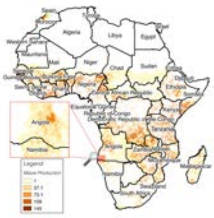
1.4 Crops production



(a) Banana



(b) Barley

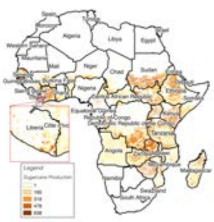


(c) Maize

(d) Oilpalm

(e) Orange

(f) Soybean



(g) Sugarcane

(h) Sunflower

(i) Tea

(j) Coffee

(k) WheatProduction

Figure 4: Crops Production.

1.5 Natural Resources

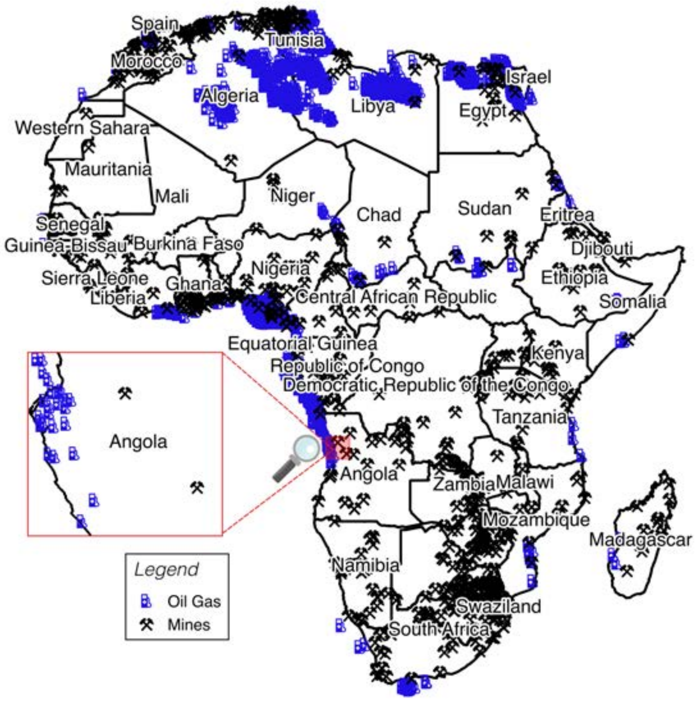
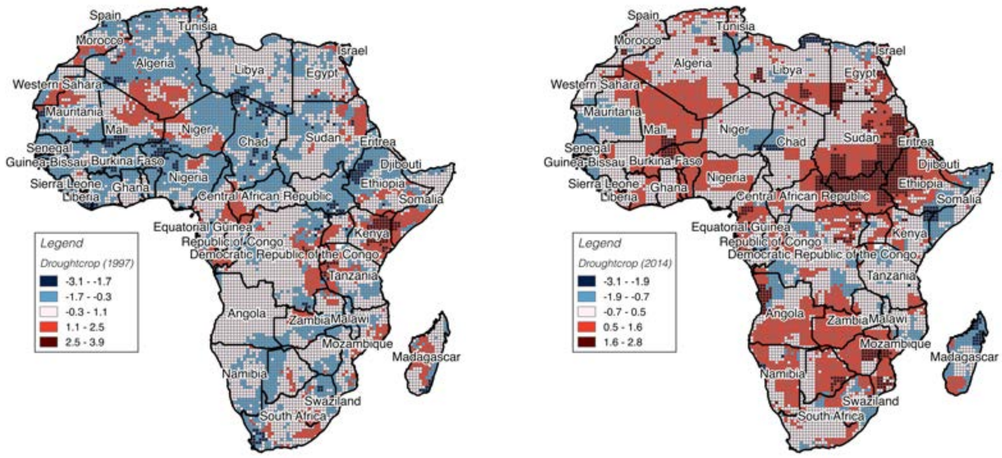


Figure 5: Natural Resources

1.6 Drought Crops. SEPI Index



(a) Drought crop 1997

(b) Drought crop 2014

Figure 6: Droughts crops

Reexamining the Role of Income Shocks and Ethnic Cleavages on Social Conflict in Africa at the Cell level.

—–Appendix C: Tables—-

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1 Descriptive Statistics

Descriptive statistics 1: Commodity Prices. Crops

Variable	Obs	Mean	Std. Dev.	Min	Max
bananas	25	1.148	.374	.691	1.82
barley	25	1.509	.615	.893	2.981
cocoa	25	1.42	.542	.713	2.469
coffe	25	1.403	.598	.677	3.065
cotton	25	.893	.277	.56	1.873
groundnuts	25	1.017	.426	.609	2.172
maize	25	1.326	.581	.807	2.731
olive oil	25	1.175	.283	.83	1.857
oranges	25	1.283	.432	.684	2.085
palm oil	25	2.198	.995	.995	4.495
rice	25	1.283	.536	.638	2.587
soybeans	25	1.333	.527	.77	2.454
sugar	25	.974	.207	.714	1.633
sunflower oil	25	1.38	.628	.628	2.806
tea	25	1.14	.26	.808	1.717
wheat	25	1.271	.437	.725	2.117
AgPrices	25	1.297	.417	.829	2.215

Descriptive statistics 2: Commodity Prices. Extractive

Variable	Obs	Mean	Std. Dev.	Min	Max
Natural gas Russian	25	2.721	1.83	.888	6.456
Natural gas Indonesian	23	2.011	1.333	.736	4.847
Natural gas Henry Hub terminal in Louisiana	24	2.761	1.49	1	6.112
Medium Price Gas	25	2.462	1.315	1	5.22
Crude Oil Price Medium	25	2.022	1.461	.569	4.569
Extprices	25	2.242	1.371	.831	4.721

Descriptive statistics 3: Commodity Prices. Mineral

Variable	Obs	Mean	Std. Dev.	Min	Max
aluminum	25	1.064	.266	.695	1.61
coal	25	1.424	.84	.653	3.433
copper	25	1.503	.952	.586	3.315
iron ore	25	3.173	3.569	.815	11.942
lead	25	1.394	.934	.503	3.186
nickel	25	1.443	.892	.522	4.19
tin	25	1.703	1.157	.667	4.281
uranium	25	2.756	2.42	.851	10.191
zinc	25	.996	.454	.513	2.152
gold	25	1.656	1.168	.707	4.354
DAP	25	1.743	1.163	.753	5.643
phosrock	25	1.95	1.811	.815	8.533
platinium	25	1.779	1.047	.763	3.646
potash	25	2.181	1.628	1	6.425
silver	25	2.196	1.846	.816	7.288
mangense	25	.949	.676	.469	3.559
MineralPrices	25	1.744	1.161	.793	4.138

Descriptive statistics 4: Commodity price shocks

Variable	Obs	Mean	Std. Dev.	Min	Max
ShockT	234036	0	.212	-3.218	3.17
ShockAgt	234036	0	.194	-3.21	3.19
ShockExt	234036	0	.06	-.48	.53
ShockMineral	234036	0	.049	-1.399	1.394

Descriptive statistics 5: Table Basic Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Drought SEPI	264568	.077	.087	0	1.5
Mines dummy	265800	.074	.262	0	1
ln(Nights Lights per capita)	221487	-9.914	4.612	-17.306	1.202
ln(Pob)	263675	7.922	4.646	-2.303	16.668
ln(Distance to the border)	259450	4.662	1.192	-5.689	6.54
ln(Distance to the capital)	265800	6.226	.79	1.309	7.575
Excluded	200216	.455	.645	0	5
Excluded dummy	200216	.534	.499	0	1
Monopoly dummy	255312	.045	.208	0	1
FRAC Index	254475	.193	.255	0	1
Polarization Index	254475	.287	.361	0	1

2 Robustness checks

2.1 Total Shock without interactions

Table C1: Total price shocks and varieties of conflict. Robustness results. Country-year trend

VARIABLES	ACLED_incidence	UCDP incidence	ACLED battle	Riots and Violence
	(1)	(2)	(3)	(4)
$ShockTotal_{(t-1)}$	0.018***	-0.006*	0.010**	0.016***
	(0.005)	(0.003)	(0.004)	(0.005)
$Excluded_{(t-1)}$	0.008**	0.003	0.002	0.006*
	(0.004)	(0.003)	(0.003)	(0.003)
$Monopoly_{(t-1)}$	0.059***	0.022***	0.036***	0.037***
	(0.013)	(0.006)	(0.011)	(0.011)
$Mines_{(t-1)}$	-0.004	-0.003	0.012	-0.013
	(0.011)	(0.006)	(0.008)	(0.010)
$DroughtSEPI_{(t-1)}$	-0.008	0.001	-0.004	-0.002
	(0.007)	(0.005)	(0.005)	(0.006)
Observations	174916	174916	174916	174916
R-squared	0.037	0.030	0.033	0.032
CONTROL VARIABLES	YES	YES	YES	YES
CELL FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Country-year trend	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definitions of ACLED database (ACLED_INCIDENCE, ACLED_BATTLES and RIOTS AND VIOLENCE) and UCDP INCIDENCE. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. p-values are reported in parentheses *** p<0.01,** p<0.05, * p<0.1

Table C2: Total price shocks and varieties of conflict. Robustness results. Shocks prices by Fdjelde

VARIABLES	ACLED_incidence	UCDP incidence	ACLED battles	Riots and Violence
	(1)	(2)	(3)	(4)
$ShockTotal_{(t-1)}$	0.024***	-0.013***	-0.004	0.024***
	(0.007)	(0.004)	(0.005)	(0.007)
$Excluded_{(t-1)}$ 0.026***	0.011***	0.022***	0.017***	
	(0.004)	(0.003)	(0.004)	(0.004)
$Monopoly_{(t-1)}$	0.152***	0.041***	0.092***	0.102***
	(0.015)	(0.006)	(0.013)	(0.013)
$Mines_{(t-1)}$	0.010	0.010	0.035***	-0.008
	(0.012)	(0.007)	(0.008)	(0.011)
$DroughtSEPI_{(t-1)}$	0.001	-0.000	0.005	0.003
	(0.007)	(0.005)	(0.006)	(0.007)
Observations	158682	158682	158682	158682
R-squared	0.007	0.001	0.004	0.006
CONTROL VARIABLES	YES	YES	YES	YES
CELL FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definitions of ACLED database (acled_incidence, acled_battles and Riots and Violence) and UCDP Incidence. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. p-values are reported in parentheses *** p<0.01,** p<0.05, * p<0.1

2.2 Disaggregated shocks without interactions

Table C3: The effect of commodity prices on conflicts: UCDP incidence. Baseline results. Period: 1990-2014

VARIABLES	UCDP incidence	UCDP incidence	UCDP incidence	UCDP incidence
	(1)	(2)	(3)	(4)
$ShockAg_{(t-1)}$	-0.009**			-0.009**
	(0.004)			(0.004)
$ShockExt_{(t-1)}$		-0.009		-0.010
		(0.006)		(0.006)
$ShockMineral_{(t-1)}$			-0.023**	-0.022**
			(0.011)	(0.011)
$Excluded_{(t-1)}$	0.008***	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
$Monopoly_{(t-1)}$	0.033***	0.033***	0.033***	0.033***
	(0.005)	(0.005)	(0.005)	(0.005)
$DroughtSEPI_{(t-1)}$	0.002	0.002	0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.005)
$Mines_{(t-1)}$	0.021***	0.021***	0.021***	0.021***
	(0.007)	(0.007)	(0.007)	(0.007)
Observations	196942	196942	196942	196942
R-squared	0.001	0.001	0.001	0.001
CONTROL VARIABLES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Control variable	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of UCDP database (INCIDENCEA). LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C4: The effect of commodity prices on conflicts: ACLED Incidence. Robustness results.

Country-year trend

VARIABLES	ACLED_incidence	ACLED_incidence	ACLED_incidence	ACLED_incidence
	(1)	(2)	(3)	(4)
$ShockAg_{(t-1)}$	0.018***			0.018***
	(0.007)			(0.007)
$ShockExt_{(t-1)}$		-0.000		0.000
		(0.009)		(0.009)
$ShockMineral_{(t-1)}$			0.055***	0.054***
			(0.020)	(0.020)
$Excluded_{(t-1)}$	0.008**	0.008**	0.008**	0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
$Monopoly_{(t-1)}$	0.059***	0.059***	0.059***	0.059***
	(0.013)	(0.013)	(0.013)	(0.013)
$DroughtSEPI_{(t-1)}$	-0.008	-0.008	-0.008	-0.008
	(0.007)	(0.007)	(0.007)	(0.007)
$Mines_{(t-1)}$	-0.004	-0.004	-0.005	-0.005
	(0.011)	(0.011)	(0.011)	(0.011)
Observations	174916	174916	174916	174916
R-squared	0.037	0.037	0.037	0.037
CONTROL VARIABLES	YES	YES	YES	YES
CELL FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Country-Year Trend	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of ACLED incidence database (ACLED_INCIDENCE). LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C5: The effect of commodity prices on conflicts: UCDP Incidence. Robustness results.

	Country-year trend			
	(1)	(2)	(3)	(4)
VARIABLES	UCDP incidence	UCDP incidence	UCDP incidence	UCDP incidence
$ShockAg_{(t-1)}$	-0.008*			-0.008*
	(0.004)			(0.004)
$ShockExt_{(t-1)}$		-0.009		-0.009
		(0.006)		(0.006)
$ShockMineral_{(t-1)}$			-0.009	-0.008
			(0.010)	(0.010)
$Excluded_{(t-1)}$	0.006**	0.006***	0.006***	0.006**
	(0.002)	(0.002)	(0.002)	(0.002)
$Monopoly_{(t-1)}$	0.015***	0.016***	0.016***	0.015***
	(0.005)	(0.005)	(0.005)	(0.005)
$DroughtSEPI_{(t-1)}$	0.002	0.002	0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.005)
$Mines_{(t-1)}$	-0.009*	-0.009	-0.009	-0.009
	(0.005)	(0.005)	(0.005)	(0.005)
Observations	205822	205822	205822	205822
R-squared	0.034	0.034	0.034	0.034
CONTROL VARIABLES	YES	YES	YES	YES
CELL FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Country-year trend	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of UCDP-GED incidence database (UCDP Incidence). LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C6: The effect of commodity prices on ACLED battles conflict and Riots and Violence against civilians. Robustness results. Country-year trend

VARIABLES	ACLED battles	ACLED battles	ACLED battles	ACLED battles	Riots and Violence	Riots and Violence	Riots and Violence	Riots and Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ShockAg_{(t-1)}$	0.013**			0.013***	0.020***			0.019***
	(0.005)			(0.005)	(0.006)			(0.006)
$ShockExt_{(t-1)}$		0.007		0.008		-0.011		-0.011
		(0.007)		(0.007)		(0.008)		(0.008)
$ShockMineral_{(t-1)}$			0.001	0.000			0.060***	0.059***
			(0.014)	(0.014)			(0.020)	(0.020)
$Excluded_{(t-1)}$	0.002	0.002	0.002	0.002	0.007*	0.006*	0.006*	0.007*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$Monopoly_{(t-1)}$	0.036***	0.036***	0.036***	0.036***	0.037***	0.037***	0.037***	0.038***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
$DroughtSEPI_{(t-1)}$	-0.003	-0.004	-0.004	-0.003	-0.002	-0.003	-0.003	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
$Mines_{(t-1)}$	0.012	0.012	0.012	0.012	-0.013	-0.013	-0.014	-0.014
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)
Observations	174916	174916	174916	174916	174916	174916	174916	174916
R-squared	0.033	0.033	0.033	0.033	0.032	0.032	0.032	0.032
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES	YES	YES
CELL FE	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Country-year trend	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of ACLED battles database (ACLED_BATTLES and RIOTS AND VIOLENCE). LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C7: The effect of commodity prices on conflicts: Total ACLED definition. Robustness results. Shocks prices by Fdjelde

VARIABLES	ACLED_incidence	UCDP incidence	ACLED battles	Riots and Violence
	(1)	(2)	(3)	(4)
$ShockAg_{(t-1)}$	0.010	-0.008**	-0.004	0.016***
	(0.006)	(0.004)	(0.005)	(0.006)
$ShockExt_{(t-1)}$	-0.004	-0.009	0.007	-0.011
	(0.008)	(0.006)	(0.007)	(0.008)
$ShockMineral_{(t-1)}$	0.044**	-0.018*	-0.007	0.045**
	(0.018)	(0.009)	(0.012)	(0.018)
$Excluded_{(t-1)}$	0.028***	0.014***	0.024***	0.017***
	(0.004)	(0.002)	(0.003)	(0.004)
$Monopoly_{(t-1)}$	0.149***	0.038***	0.091***	0.099***
	(0.015)	(0.006)	(0.012)	(0.012)
$DroughtSEPI_{(t-1)}$	0.001	0.004	0.005	0.003
	(0.007)	(0.005)	(0.006)	(0.007)
$Mines_{(t-1)}$	0.009	0.015**	0.035***	-0.008
	(0.012)	(0.006)	(0.008)	(0.011)
Observations	158682	196074	158682	158682
R-squared	0.007	0.001	0.004	0.007
0.007				
CONTROL VARIABLES	YES	YES	YES	YES
CELL FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definitions of ACLED database (ACLED_INCIDENCE, ACLED_BATTLES and RIOTS AND VIOLENCE) and UCDP INCIDENCE. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. p-values are reported in parentheses *** p<0.01,** p<0.05, * p<0.1

2.3 Disaggregated shocks

2.3.1 Country-year trend fixed effects

Table C8: The effect of commodity prices and ethnic cleavages on conflicts: ACLED Incidence. Robustness results. Country-year trend.

VARIABLES	ACLED_incidence	ACLED_incidence	ACLED_incidence	ACLED_incidence
	(1)	(2)	(3)	(4)
$ShockAg_{(t-1)}$	0.021**			0.019**
	(0.009)			(0.009)
$ShockExt_{(t-1)}$		0.019		0.018
		(0.015)		(0.015)
$ShockMineral_{(t-1)}$			0.091***	0.089***
			(0.032)	(0.032)
$Excluded_{(t-1)}$	0.008**	0.008**	0.008*	0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
$Monopoly_{(t-1)}$	0.052***	0.061***	0.061***	0.053***
	(0.013)	(0.014)	(0.014)	(0.013)
$ShockAg_{(t-1)} * excluded_{(t-1)}$	-0.004			-0.003
	(0.009)			(0.009)
$ShockExt_{(t-1)} * excluded_{(t-1)}$		-0.044**		-0.042**
		(0.019)		(0.019)
$ShockMineral_{(t-1)} * excluded_{(t-1)}$			-0.029	-0.029
			(0.042)	(0.042)
$ShockAg_{(t-1)} * monopoly_{(t-1)}$	-0.106***			-0.103***
	(0.039)			(0.039)
$ShockExt_{(t-1)} * monopoly_{(t-1)}$		-0.033		-0.024
		(0.023)		(0.023)
$ShockMineral_{(t-1)} * monopoly(t-1)$			0.148	0.121
			(0.197)	(0.200)
$ShockAg_{(t-1)} * EthnicPol$	-0.048**			-0.050**
	(0.021)			(0.021)
$ShockExt_{(t-1)} * EthnicPol$		0.031		0.029
		(0.035)		(0.035)
$ShockMineral_{(t-1)} * EthnicPol$			-0.290**	-0.297**
			(0.132)	(0.133)
$ShockAg_{(t-1)} * EFractional$	0.078**			0.082**
	(0.032)			(0.032)
$ShockExt_{(t-1)} * EFractional$		0.020		0.025
		(0.029)		(0.029)
$ShockMineral_{(t-1)} * EFractional$			0.359	0.375*
			(0.220)	(0.221)
$DroughtSEPI_{(t-1)}$	-0.001	-0.003	-0.002	-0.001
	(0.010)	(0.010)	(0.010)	(0.010)
$DroughtSEPI_{(t-1)} * excluded_{(t-1)}$	-0.014	-0.013	-0.014	-0.014
	(0.013)	(0.013)	(0.013)	(0.013)
$Mines_{(t-1)}$	-0.011	-0.012	-0.013	-0.013
	(0.012)	(0.012)	(0.012)	(0.012)
$Mines_{(t-1)} * excluded_{(t-1)}$	-0.011	-0.012	-0.013	-0.013
	(0.012)	(0.012)	(0.012)	(0.012)
Observations	167368	167368	167368	167368
R-squared	0.037	0.037	0.037	0.038

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of ACLED incidence database (ACLED_INCIDENCE). LPM estimations. Conley (2008) standard errors in parentheses , allowing for spatial correlation within a 100km radius and for two periods of correlation. Cell, country, country-year trend and year fixed effects. Control variables. p-values are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C9: The effect of commodity prices and ethnic cleavages on conflicts: UCDP Incidence. Robustness results. Country-year trend.

VARIABLES	UCDP Incidence	UCDP Incidence	UCDP Incidence	UCDP Incidence
	(1)	(2)	(3)	(4)
$ShockAg_{(t-1)}$	-0.016***			-0.016***
	(0.005)			(0.006)
$ShockExt_{(t-1)}$		-0.016		-0.016
		(0.012)		(0.012)
$ShockMineral_{(t-1)}$			-0.004	-0.002
			(0.013)	(0.013)
$Excluded_{(t-1)}$	0.005**	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
$Monopoly_{(t-1)}$	0.014***	0.016***	0.016***	0.014***
	(0.004)	(0.005)	(0.005)	(0.004
$ShockAg_{(t-1)} * excluded_{(t-1)}$	0.002			0.002
	(0.006)			(0.006)
$ShockExt_{(t-1)} * excluded_{(t-1)}$		-0.002		-0.002
		(0.013)		(0.013)
$ShockMineral_{(t-1)} * excluded_{(t-1)}$			-0.005	-0.006
			(0.023)	(0.023)
$ShockAg_{(t-1)} * monopoly_{(t-1)}$	-0.038**			-0.039**
	(0.016)			(0.016))
$ShockExt_{(t-1)} * monopoly_{(t-1)}$		0.024**		0.024*
		(0.012)		(0.012)
$ShockMineral_{(t-1)} * monopoly_{(t-1)}$			-0.165	-0.167
			(0.305)	(0.306)
$ShockAg_{(t-1)} * EthnicPol$	-0.008			-0.008
	(0.013)			(0.013)
$ShockExt_{(t-1)} * EthnicPol$		0.003		0.003
		(0.027)		(0.027)
$ShockMineral_{(t-1)} * EthnicPol$			-0.021	-0.027
			(0.065)	(0.065)
$ShockAg_{(t-1)} * EFractional$	0.042**			0.042**
	(0.017)			(0.017)
$ShockExt_{(t-1)} * EFractional$		0.029		0.029
		(0.021)		(0.021)
$ShockMineral_{(t-1)} * EFractional$			0.063	0.069
			(0.092)	(0.092)
$DroughtSEPI_{(t-1)}$	0.003	0.003	0.002	0.003
	(0.006)	(0.006)	(0.006)	(0.006)
$DroughtSEPI_{(t-1)} * excluded_{(t-1)}$	0.001	0.001	0.001	0.001
	(0.009)	(0.009)	(0.009)	(0.009)
$Mines_{(t-1)}$	-0.016**	-0.016**	-0.016**	-0.016**
	(0.007)	(0.007)	(0.007)	(0.007)
$Mines_{(t-1)} * excluded_{(t-1)}$	0.016*	0.016*	0.016*	0.016*
	(0.009)	(0.009)	(0.009)	(0.009)
Observations	196942	196942	196942	196942
R-squared	0.034	0.034	0.034	0.034

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of UCDP database (UCDP Incidence). LPM estimations. Conley (2008) standard errors in parentheses , allowing for spatial correlation within a 100km radius and for two periods of correlation. Cell, country, country-year trend and year fixed effects. Control variables. p-values are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C10: The effect of commodity prices and ethnic cleavages on conflicts: ACLED battles and Riots and Violence against civilians. Robustness results. Country-year trend.

VARIABLES	ACLED battles (1)	ACLED battles (2)	ACLED battles (3)	ACLED battles (4)	Riots and Violence (5)	Riots and Violence (6)	Riots and Violence (7)	Riots and Violence (8)
$ShockAg_{(t-1)}$	0.007			0.008	0.022**			0.019**
	(0.007)			(0.007)	(0.009)			(0.009)
$ShockExt_{(t-1)}$		0.001		0.001		0.005		0.004
		(0.013)		(0.013)		(0.013)		(0.013)
$ShockMineral_{(t-1)}$			-0.020	-0.020			0.105***	0.103***
			(0.019)	(0.019)			(0.030)	(0.030)
$Excluded_{(t-1)}$	0.003	0.002	0.002	0.003	0.008**	0.007**	0.007**	0.008**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$Monopoly_{(t-1)}$	0.032***	0.037***	0.039***	0.033***	0.036***	0.038***	0.038***	0.036***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
$ShockAg_{(t-1)} * excluded_{(t-1)}$	0.002			0.002	-0.004			-0.002
	(0.007)			(0.007)	(0.008)			(0.008)
$ShockExt_{(t-1)} * excluded_{(t-1)}$			0.038	0.038			-0.047	-0.046
			(0.031)	(0.031)			(0.040)	(0.040)
$ShockMineral_{(t-1)} * excluded_{(t-1)}$		-0.013		-0.012		-0.042**		-0.041**
		(0.017)		(0.017)		(0.017)		(0.017)
$ShockAg_{(t-1)} * monopoly_{(t-1)}$	-0.066**			-0.067**	-0.034			-0.032
	(0.030)			(0.030)	(0.035)			(0.035)
$ShockExt_{(t-1)} * monopoly_{(t-1)}$		0.021		0.029*		-0.017		-0.013
		(0.017)		(0.017)		(0.021)		(0.021)
$ShockMineral_{(t-1)} * monopoly_{(t-1)}$			0.420	0.419			-0.005	-0.021
			(0.291)	(0.293)			(0.217)	(0.220)
$ShockAg_{(t-1)} * EthnicPol$	-0.016			-0.017	-0.043**			-0.045**
	(0.016)			(0.016)	(0.020)			(0.020)
$ShockExt_{(t-1)} * EthnicPol$		0.026		0.024		0.011		0.008
		(0.031)		(0.031)		(0.034)		(0.034)
$ShockMineral_{(t-1)} * EthnicPol$			0.067	0.060			-0.327**	-0.332**
			(0.065)	(0.065)			(0.135)	(0.136)
$ShockAg_{(t-1)} * EFractional$	0.052**			0.051**	0.072**			0.075**
	(0.024)			(0.024)	(0.031)			(0.031)
$ShockExt_{(t-1)} * EFractional$		0.033		0.034		0.042		0.047
		(0.022)		(0.022)		(0.029)		(0.029)
$ShockMineral_{(t-1)} * EFractional$			-0.081	-0.074			0.411*	0.421*
			(0.094)	(0.094)			(0.226)	(0.227)
$DroughtSEPI_{(t-1)}$	0.005	0.004	0.004	0.005	0.006	0.005	0.005	0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)
Drought SEPI$_{(t-1)} * excluded_{(t-1)}$	-0.015	-0.016	-0.015	-0.016	-0.015	-0.015	-0.016	-0.015
	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)	(0.012)	(0.012)
$Mines_{(t-1)}$	0.007	0.007	0.007	0.008	-0.014	-0.014	-0.015	-0.015
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)
$Mines_{(t-1)} * excluded_{(t-1)}$	0.011	0.011	0.011	0.011	0.001	0.001	0.003	0.003
	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	167368	167368	167368	167368	167368	167368	167368	167368
R-squared	0.034	0.034	0.034	0.034	0.032	0.032	0.032	0.032

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of ACLED battles database (ACLED_BATTLES and RIOTS AND VIOLENCE). LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

2.3.2 Alternative measure of shocks

Table C11: The effect of commodity prices and ethnic cleavages on conflicts: Robustness results.

Shocks prices by Fdjelde.

VARIABLES	ACLED_incidence	UCDP incidence	ACLED battle	Riots and Violence
	(1)	(2)	(3)	(4)
$ShockAg_{(t-1)}$	0.019**	-0.013**	-0.005	0.023***
	(0.009)	(0.005)	(0.006)	(0.008)
$ShockExt_{(t-1)}$	0.011	-0.013	-0.000	0.003
	(0.012)	(0.010)	(0.011)	(0.011)
$ShockMineral_{(t-1)}$	0.070**	-0.008	-0.014	0.072***
	(0.029)	(0.011)	(0.015)	(0.027)
$Excluded_{(t-1)}$	0.026***	0.011***	0.022***	0.017***
	(0.004)	(0.003)	(0.004)	(0.004)
$Monopoly_{(t-1)}$	0.151***	0.040***	0.090***	0.102***
	(0.015)	(0.006)	(0.012)	(0.013)
$ShockAg_{(t-1)} * excluded_{(t-1)}$	-0.009	0.008	0.006	-0.010
	(0.011)	(0.007)	(0.008)	(0.010)
$ShockExt_{(t-1)} * excluded_{(t-1)}$	-0.027	-0.009	-0.002	-0.031**
	(0.017)	(0.012)	(0.015)	(0.016)
$ShockMineral_{(t-1)} * excluded_{(t-1)}$	-0.011	0.008	0.018	-0.018
	(0.039)	(0.020)	(0.025)	(0.038)
$ShockAg_{(t-1)} * monopoly_{(t-1)}$	-0.108**	-0.028*	-0.103***	-0.044
	(0.044)	(0.017)	(0.033)	(0.040)
$ShockExt_{(t-1)} * monopoly_{(t-1)}$	-0.034	0.026**	0.028*	-0.024
	(0.021)	(0.013)	(0.016)	(0.020)
$ShockMineral_{(t-1)} * monopoly_{(t-1)}$	-0.344*	-0.197	-0.281	-0.241
	(0.190)	(0.320)	(0.248)	(0.216)
$ShockAg_{(t-1)} * EthnicPol$	-0.033	-0.008	-0.015	-0.017
	(0.020)	(0.013)	(0.015)	(0.019)
$ShockExt_{(t-1)} * EthnicPol$	0.017	0.003	0.003	0.005
	(0.034)	(0.028)	(0.029)	(0.032)
$ShockMineral_{(t-1)} * EthnicPol$	-0.202*	-0.010	0.030	-0.199*
	(0.112)	(0.062)	(0.055)	(0.113)
$ShockAg_{(t-1)} * EFractional$	0.029	0.034	0.029	0.008
	(0.030)	(0.021)	(0.021)	(0.028)
$ShockExt_{(t-1)} * EFractional$	0.016	0.002	0.025	0.034
	(0.032)	(0.022)	(0.023)	(0.031)
$ShockMineral_{(t-1)} * EFractional$	0.230	0.001	-0.035	0.226
	(0.187)	(0.093)	(0.089)	(0.187)
$Drought_{(t-1)}$	-0.004	-0.002	0.001	0.003
	(0.011)	(0.006)	(0.008)	(0.010)
$Drought_{(t-1)} * excluded_{(t-1)}$	0.010	0.005	0.009	0.002
	(0.014)	(0.009)	(0.011)	(0.013)
$Mines_{(t-1)}$	0.003	0.005	0.032***	-0.012
	(0.013)	(0.008)	(0.010)	(0.013)
$Mines_{(t-1)} * excluded_{(t-1)}$	0.018	0.012	0.010	0.009
	(0.015)	(0.010)	(0.013)	(0.015)
Observations	151593	151593	151593	151593
R-squared	0.007	0.006	0.007	0.007

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following
for conflicts following the definition of ACLED incidence database (ACLED_INCIDENCE).
LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation
within a 100km radius and for two periods of correlation. Cell, country and year fixed effects.
Control variables. p-values are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1

2.3.3 Additional control variables

Table C12: The effect of commodity prices and ethnic cleavages on conflicts Robustness results.

Growing-sesion drought crops

VARIABLES	ACLED_incidence	UCDP incidence	ACLED battle	Riots and Violence
	(1)	(2)	(3)	(4)
$ShockAg_{(t-1)}$	0.041***	-0.013**	0.001	0.043***
	(0.009)	(0.005)	(0.007)	(0.009)
$ShockExt_{(t-1)}$	0.019	-0.019*	0.005	0.004
	(0.015)	(0.012)	(0.013)	(0.013)
$ShockMineral_{(t-1)}$	0.133***	-0.007	-0.019	0.142***
	(0.033)	(0.013)	(0.019)	(0.031)
$Excluded_{(t-1)}$	0.020***	0.005**	0.017***	0.013***
	(0.004)	(0.002)	(0.003)	(0.003)
$Monopoly_{(t-1)}$	0.125***	0.027***	0.073***	0.088***
	(0.014)	(0.004)	(0.011)	(0.012)
$ShockAg_{(t-1)} * excluded_{(t-1)}$	-0.033***	0.003	-0.006	-0.024***
	(0.009)	(0.006)	(0.007)	(0.008)
$ShockExt_{(t-1)} * excluded_{(t-1)}$	-0.038**	-0.002	-0.018	-0.035**
	(0.019)	(0.013)	(0.017)	(0.018)
$ShockMineral_{(t-1)} * excluded_{(t-1)}$	-0.071*	-0.017	0.008	-0.081**
	(0.042)	(0.023)	(0.032)	(0.040)
$ShockAg_{(t-1)} * monopoly_{(t-1)}$	-0.231***	-0.099***	-0.176***	-0.114***
	(0.039)	(0.018)	(0.030)	(0.035)
$ShockExt_{(t-1)} * monopoly_{(t-1)}$	-0.026	0.024*	0.021	-0.014
	(0.023)	(0.012)	(0.017)	(0.022)
$ShockMineral_{(t-1)} * monopoly_{(t-1)}$	-0.077	-0.533	0.055	-0.227
	(0.178)	(0.358)	(0.263)	(0.211)
$ShockAg_{(t-1)} * EthnicPol$	-0.061***	-0.012	-0.015	-0.057***
	(0.022)	(0.013)	(0.016)	(0.020)
$ShockExt_{(t-1)} * EthnicPol$	0.031	0.009	0.030	0.009
	(0.037)	(0.029)	(0.032)	(0.036)
$ShockMineral_{(t-1)} * EthnicPol$	-0.298**	-0.060	0.067	-0.347**
	(0.133)	(0.069)	(0.066)	(0.138)
$ShockAg_{(t-1)} * EFractional$	0.072**	0.047**	0.033	0.068**
	(0.033)	(0.021)	(0.024)	(0.031)
$ShockExt_{(t-1)} * EFractional$	0.024	0.026	0.032	0.048
	(0.034)	(0.021)	(0.023)	(0.033)
$ShockMineral_{(t-1)} * EFractional$	0.326	0.083	-0.099	0.402*
	(0.222)	(0.095)	(0.096)	(0.230)
$Drought_{(t-1)}$	-0.005	-0.010	0.001	-0.002
	(0.010)	(0.006)	(0.007)	(0.009)
$Drought_{(t-1)} * excluded_{(t-1)}$	0.015	0.023***	0.006	0.009
	(0.014)	(0.009)	(0.010)	(0.012)
$DroughtCROPSEPI_{(t-1)}$	0.000	0.001**	0.000	-0.000
	(0.001)	(0.000)	(0.001)	(0.001)
$DroughtCROPSEPI_{(t-1)} * excluded_{(t-1)}$	0.004***	-0.000	0.001	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
$Mines_{(t-1)}$	0.006	0.016**	0.035***	-0.005
	(0.013)	(0.008)	(0.010)	(0.012)
$Mines_{(t-1)} * excluded_{(t-1)}$	0.018	0.010	0.012	0.005
	(0.015)	(0.009)	(0.012)	(0.014)
Observations	167368	196942	167368	167368
R-squared	0.007	0.002	0.004	0.007

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definitions of ACLED database (ACLED_INCIDENCE, ACLED_BATTLES and RIOTS AND VIOLENCE) and UCDP INCIDENCE. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. Cell, country and year fixed effects. Control variables are included. p-values are reported parentheses *** p<0.01,** p<0.05, * p<0.1

Table C13: The effect of commodity prices and ethnic cleavages on conflicts: Riots and Violence against civilians. Robustness results. Urban riots and violence

VARIABLES	Riots and violence (1)	Riots and violence (2)	Riots and violence (3)	Riots and violence (4)
$ShockAg_{(t-1)}$	0.040***			0.036***
	(0.008)			(0.008)
$ShockAg_{(t-1)}$* $Urban_{(t-1)}$	0.023**			0.027**
	(0.011)			(0.011
$ShockExt_{(t-1)}$		0.004		0.003
		(0.013)		(0.013)
$ShockExt_{(t-1)}$*$Urban_{(t-1)}$		-0.010		-0.017
		(0.015)		(0.015)
$ShockMineral_{(t-1)}$			0.149***	0.142***
			(0.031)	(0.031)
$ShockMineral_{(t-1)}$ *$Urban_{(t-1)}$			-0.016	-0.023
			(0.015)	(0.015)
$Excluded_{(t-1)}$	0.013***	0.013***	0.013***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)
$Monopoly_{(t-1)}$	0.092***	0.103***	0.102***	0.091***
	(0.012)	(0.012)	(0.012)	(0.012)
$ShockAg_{(t-1)} * excluded_{(t-1)}$	-0.021**			-0.019**
	(0.008)			(0.008)
$ShockExt_{(t-1)} * excluded_{(t-1)}$		-0.031*		-0.028
		(0.018)		(0.018)
$ShockMineral_{(t-1)} * excluded_{(t-1)}$			-0.085**	-0.081**
			(0.040)	(0.040)
$ShockAg_{(t-1)} * monopoly_{(t-1)}$	-0.130***			-0.128***
	(0.035)			(0.035)
$ShockExt_{(t-1)} * monopoly_{(t-1)}$		-0.014		-0.005
		(0.021)		(0.021)
$ShockMineral_{(t-1)} * monopoly_{(t-1)}$			-0.191	-0.182
			(0.204)	(0.208)
$ShockAg_{(t-1)} * EthnicPol$	-0.057***			-0.058***
	(0.021)			(0.020)
$ShockExt_{(t-1)} * EthnicPol$		-0.002		-0.003
		(0.037)		(0.037)
$ShockMineral_{(t-1)} * EthnicPol$			-0.316**	-0.319**
			(0.135)	(0.136)
$ShockAg_{(t-1)} * EFractional$	0.067**			0.071**
	(0.031)			(0.031)
$ShockExt_{(t-1)} * EFractional$		0.043		0.049
		(0.036)		(0.035)
$ShockMineral_{(t-1)} * EFractional$			0.356	0.375*
			(0.225)	(0.227)
$Drought_{(t-1)}$	-0.004	-0.006	-0.006	-0.004
	(0.009)	(0.009)	(0.009)	(0.009)
$Drought_{(t-1)} * excluded_{(t-1)}$	0.007	0.008	0.007	0.008
	(0.012)	(0.012)	(0.012)	(0.012)
$Mines_{(t-1)}$	-0.001	-0.002	-0.004	-0.002
	(0.012)	(0.012)	(0.012)	(0.012)
$Mines_{(t-1)} * excluded_{(t-1)}$	0.001	0.002	0.005	0.004
	(0.014)	(0.014)	(0.014)	(0.014)
$Urban_{(t-1)}$	0.026***	0.029***	0.029***	0.026***
	(0.008)	(0.008)	(0.008)	(0.008)
Observations	163744	163744	163744	163744
R-squared	0.007	0.007	0.007	0.008

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definitions of ACLED database (RIOTS AND VIOLENCE)LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. Cell, country and year fixed effects. Control variables are included. p-values are reported. in parentheses *** p<0.01,** p<0.05, * p<0.1

2.3.4 Conflict Onset, Offset

Table C14: Conflict Onset, Offset with total commodity prices and types of conflicts

VARIABLES	ACLED Onset	UCDP Onset	Battles Onset	R&V Onset	ACLED Offset	UCDP Offset	Battles Offset	R&V Offset
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ShockTotal(t-1)$	0.034***	-0.003	0.006	0.029***	0.012	0.100	-0.070	-0.013
	(0.007)	(0.004)	(0.005)	(0.006)	(0.043)	(0.081)	(0.078)	(0.047)
$Excluded_{(t-1)}$	0.001	-0.001	0.002	0.002	0.030	-0.018	0.013	0.037
	(0.003)	(0.002)	(0.002)	(0.003)	(0.023)	(0.041)	(0.036)	(0.027)
$Monopoly_{(t-1)}$	0.049***	0.020***	0.038***	0.040***	-0.106*	-0.025	0.048	-0.114
	(0.009)	(0.004)	(0.008)	(0.008)	(0.063)	(0.130)	(0.096)	(0.070)
$ShockTotal(t-1) * excluded_{(t-1)}$	-0.022***	-0.002	-0.005	-0.023***	0.037	-0.270***	0.012	0.017
	(0.007)	(0.004)	(0.005)	(0.007)	(0.044)	(0.081)	(0.072)	(0.050)
$ShockTotal(t-1) * monopoly_{(t-1)}$	-0.068***	-0.031***	-0.035***	-0.053***	0.004	-0.080	0.132	0.036
	(0.016)	(0.008)	(0.012)	(0.014)	(0.098)	(0.203)	(0.177)	(0.099)
$ShockTotal(t-1) * EthnicPol$	-0.044***	-0.026***	-0.013	-0.036**	-0.033	0.232	-0.283	0.008
	(0.016)	(0.009)	(0.011)	(0.015)	(0.173)	(0.339)	(0.275)	(0.202)
$ShockTotal(t-1) * EFractional$	0.044*	0.039***	0.026	0.045**	0.139	-0.388	0.617	0.061
	(0.023)	(0.013)	(0.016)	(0.023)	(0.277)	(0.531)	(0.436)	(0.328)
$DroughtSEPI_{(t-1)}$	-0.016*	-0.011**	0.004	-0.016**	0.151**	0.062	-0.135	0.184***
	(0.009)	(0.004)	(0.006)	(0.008)	(0.061)	(0.143)	(0.115)	(0.067)
$DroughtSEPI_{(t-1)} * excluded_{(t-1)}$	0.020*	0.018**	0.004	0.012	-0.211**	-0.118	-0.047	-0.149
	(0.011)	(0.007)	(0.009)	(0.010)	(0.083)	(0.172)	(0.135)	(0.094)
$Mines_{(t-1)}$ -0.018*	0.005	0.008	-0.020*	-0.111*	0.223*	-0.167*	-0.059	
	(0.011)	(0.006)	(0.007)	(0.010)	(0.058)	(0.135)	(0.097)	(0.061)
$Mines_{(t-1)} * excluded_{(t-1)}$	-0.003	0.012*	-0.001	-0.007	-0.108***	-0.013	-0.198***	-0.097**
	(0.012)	(0.007)	(0.009)	(0.012)	(0.040)	(0.067)	(0.063)	(0.043)
Observations	167368	196942	167368	167368	13751	5228	6894	10734
R-squared	0.001	0.001	0.001	0.001	0.005	0.008	0.006	0.004

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of ACLED database (ACLED_ONSET, BATTLES_ONSET and R&V ONSET) and (ACLED_OFFSET , BATTLES_ONFFSET and R&V OFFSET) and the UCDP database(UCDP ONSET and UCDP OFFSET). LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C15: Conflict Onset, Offset with disaggregated commodity price shocks and types of conflicts

VARIABLES	ACLED Onset	UCDP Onset	Battles Onset	R&V Onset	ACLED Offset	UCDP Offset	Battles Offset	R&V Offset
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ShockAg_{(t-1)}$	0.028***	-0.002	0.003	0.025***	0.077	0.158	0.031	0.055
	(0.008)	(0.004)	(0.006)	(0.007)	(0.060)	(0.114)	(0.099)	(0.067)
$ShockExt_{(t-1)}$	0.023*	-0.011	0.009	0.008	-0.085	0.030	-0.304	-0.326**
	(0.013)	(0.009)	(0.012)	(0.011)	(0.128)	(0.149)	(0.221)	(0.128)
$ShockMineral_{(t-1)}$	0.071**	-0.006	-0.011	0.075***	-0.086	0.162	-0.037	-0.000
	(0.030)	(0.011)	(0.019)	(0.028)	(0.095)	(0.376)	(0.193)	(0.093)
$Excluded_{(t-1)}$	0.001	-0.001	0.002	0.002	0.030	-0.020	0.007	0.035
	(0.003)	(0.002)	(0.002)	(0.003)	(0.024)	(0.041)	(0.036)	(0.027)
$Monopoly_{(t-1)}$	0.043***	0.017***	0.031***	0.037***	-0.119*	0.030	0.030	-0.146**
	(0.008)	(0.004)	(0.008)	(0.008)	(0.064)	(0.146)	(0.096)	(0.073)
$ShockAg_{(t-1)} * excluded_{(t-1)}$	-0.017**	-0.001	-0.005	-0.019***	0.009	-0.296***	-0.048	-0.006
	(0.008)	(0.005)	(0.006)	(0.007)	(0.055)	(0.098)	(0.085)	(0.063)
$ShockExt_{(t-1)} * excluded_{(t-1)}$	-0.032**	-0.003	-0.009	-0.028*	0.059	-0.197	0.189	0.195
	(0.016)	(0.011)	(0.015)	(0.015)	(0.133)	(0.185)	(0.219)	(0.141)
$ShockMineral_{(t-1)} * excluded_{(t-1)}$	0.005	0.001	0.023	-0.007	0.258**	-0.088	0.395	0.165
	(0.038)	(0.018)	(0.029)	(0.037)	(0.122)	(0.418)	(0.293)	(0.132)
$ShockAg_{(t-1)} * monopoly_{(t-1)}$	-0.123***	-0.080***	-0.116***	-0.081***	-0.135	0.036	0.283	-0.228
	(0.031)	(0.015)	(0.024)	(0.027)	(0.144)	(0.319)	(0.222)	(0.147)
$ShockExt_{(t-1)} * monopoly_{(t-1)}$	-0.031	0.012	0.002	-0.023	0.242	-1.080	0.850**	0.540***
	(0.019)	(0.010)	(0.015)	(0.017)	(0.194)	(0.664)	(0.369)	(0.190)
$ShockMineral_{(t-1)} * monopoly_{(t-1)}$	0.109	-0.312	0.299	0.209	-0.086	-0.253	-0.721	0.119
	(0.232)	(0.263)	(0.297)	(0.226)	(0.298)	(0.705)	(0.605)	(0.325)
$ShockAg_{(t-1)} * EthnicPol$	-0.052***	-0.033***	-0.027**	-0.042**	-0.004	0.144	-0.248	-0.007
	(0.020)	(0.011)	(0.014)	(0.019)	(0.205)	(0.416)	(0.334)	(0.252)
$ShockExt_{(t-1)} * EthnicPol$	0.040	0.026	0.053**	0.026	-0.553	0.798	-0.885	0.182
	(0.031)	(0.024)	(0.026)	(0.029)	(0.669)	(0.706)	(0.723)	(0.664)
$ShockMineral_{(t-1)} * EthnicPol$	-0.314**	-0.100**	0.044	-0.275**	0.106	-0.972	0.147	0.018
	(0.135)	(0.045)	(0.057)	(0.129)	(0.532)	(1.733)	(1.267)	(0.512)
$ShockAg_{(t-1)} * EFractional$	0.046	0.055***	0.040**	0.043	0.055	-0.328	0.733	0.006
	(0.030)	(0.016)	(0.021)	(0.029)	(0.319)	(0.628)	(0.521)	(0.399)
$ShockExt_{(t-1)} * EFractional$	-0.023	-0.012	-0.022	-0.001	0.776	-1.385	1.010	-0.151
	(0.020)	(0.017)	(0.019)	(0.018)	(1.057)	(1.079)	(0.956)	(1.002)
$ShockMineral_{(t-1)} * EFractional$	0.491**	0.128*	-0.022	0.419*	0.182	1.614	0.199	0.135
	(0.231)	(0.067)	(0.081)	(0.223)	(0.880)	(3.007)	(2.263)	(0.817)
$DroughtSEPI_{(t-1)}$	-0.015*	-0.010**	0.005	-0.015*	0.155**	0.059	-0.144	0.195***
	(0.009)	(0.004)	(0.006)	(0.008)	(0.061)	(0.143)	(0.115)	(0.067)
$DroughtSEPI_{(t-1)} * excluded_{(t-1)}$	0.019	0.018**	0.002	0.011	-0.215***	-0.114	-0.042	-0.156*
	(0.011)	(0.007)	(0.009)	(0.010)	(0.083)	(0.173)	(0.136)	(0.094)
$Mines_{(t-1)}$	-0.019*	0.005	0.007	-0.021**	-0.108*	0.220	-0.159	-0.059
	(0.011)	(0.006)	(0.007)	(0.010)	(0.058)	(0.135)	(0.098)	(0.061)
$Mines_{(t-1)} * excluded_{(t-1)}$	-0.002	0.011*	-0.001	-0.006	-0.119***	-0.012	-0.213***	-0.101**
	(0.012)	(0.007)	(0.009)	(0.012)	(0.041)	(0.068)	(0.062)	(0.043)
Observations	167368	196942	167368	167368	13751	5228	6894	10734
R-squared	0.002	0.001	0.001	0.001	0.005	0.010	0.010	0.005

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of ACLED database (ACLED_ONSET, BATTLES_ONSET and R&V ONSET) and (ACLED_OFFSET , BATTLES_ONFFSET and R&V OFFSET) and the UCDP database(UCDP ONSET and UCDP OFFSET). LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

2.3.5 Alternative definition of cell area

Table C16: The effect of commodity prices and ethnic cleavages on conflicts Robustness results.

Grid panel 110 x 110

VARIABLES	ACLED_incidence	UCDP incidence	ACLED battle	Riots and Violence
	(1)	(2)	(3)	(4)
$ShockAg_{(t-1)}$	0.125***	-0.025	0.036*	0.128***
	(0.027)	(0.018)	(0.021)	(0.025)
$ShockExt_{(t-1)}$	0.057*	-0.013	0.049*	0.006
	(0.031)	(0.026)	(0.029)	(0.028)
$ShockMineral_{(t-1)}$	0.096**	-0.035	0.030	0.051
	(0.038)	(0.024)	(0.029)	(0.038)
$Excluded_{(t-1)}$	0.036***	-0.005	0.027***	0.037***
	(0.009)	(0.006)	(0.009)	(0.009)
$Monopoly_{(t-1)}$	0.226***	0.077***	0.142***	0.187***
	(0.023)	(0.012)	(0.022)	(0.021)
$ShockAg_{(t-1)} * excluded_{(t-1)}$	-0.079***	0.004	-0.052**	-0.046**
	(0.026)	(0.018)	(0.022)	(0.023)
$ShockExt_{(t-1)} * excluded_{(t-1)}$	-0.090**	-0.032	-0.042	-0.091***
	(0.038)	(0.027)	(0.034)	(0.035)
$ShockMineral_{(t-1)} * excluded_{(t-1)}$	-0.038	0.057*	0.024	-0.058
	(0.046)	(0.030)	(0.033)	(0.044)
$ShockAg_{(t-1)} * monopoly_{(t-1)}$	-0.379***	-0.155***	-0.294***	-0.260***
	(0.056)	(0.033)	(0.046)	(0.052)
$ShockExt_{(t-1)} * monopoly_{(t-1)}$	-0.102**	0.040	-0.042	-0.036
	(0.047)	(0.028)	(0.038)	(0.044)
$ShockMineral_{(t-1)} * monopoly_{(t-1)}$	0.071	0.041	-0.056	0.086
	(0.090)	(0.059)	(0.082)	(0.086)
$ShockAg_{(t-1)} * EthnicPol$	-0.288***	0.038	-0.163**	-0.279***
	(0.092)	(0.061)	(0.073)	(0.086)
$ShockExt_{(t-1)} * EthnicPol$	0.001	-0.126	-0.154	0.136
	(0.147)	(0.119)	(0.125)	(0.137)
$ShockMineral_{(t-1)} * EthnicPol$	0.030	0.002	0.080	0.091
	(0.171)	(0.068)	(0.100)	(0.167)
$ShockAg_{(t-1)} * EFractional$	0.365***	0.081	0.198**	0.302***
	(0.108)	(0.071)	(0.078)	(0.101)
$ShockExt_{(t-1)} * EFractional$	0.081	0.060	0.032	0.081
	(0.079)	(0.057)	(0.060)	(0.072)
$ShockMineral_{(t-1)} * EFractional$	-0.097	-0.075	-0.232*	-0.073
	(0.255)	(0.091)	(0.128)	(0.249)
$Drought_{(t-1)}$	0.007	-0.006	0.023	-0.008
	(0.030)	(0.019)	(0.024)	(0.028)
$Drought_{(t-1)} * excluded_{(t-1)}$	0.048	0.062**	0.020	0.066*
	(0.038)	(0.026)	(0.032)	(0.036)
$Mines_{(t-1)}$	0.010	0.014	0.047***	0.009
	(0.018)	(0.011)	(0.015)	(0.017)
$Mines_{(t-1)} * excluded_{(t-1)}$	0.013**	0.010***	0.015***	0.001
	(0.005)	(0.004)	(0.005)	(0.005)
Observations	44964	52458	44964	44964
R-squared	0.011	0.006	0.012	0.011

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definitions of ACLED database (ACLED_INCIDENCE, ACLED_BATTLES and RIOTS AND VIOLENCE) and UCDP INCIDENCE. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. Cell, country and year fixed effects. Control variables are included p-values are reported parentheses *** p<0.01,** p<0.05, * p<0.1

2.3.6 Alternative spatial temporal kernels standard errors

Table C17: Alternative spatial temporal kernels standard errors.

VARIABLES	ACLED_incidence	UCDP incidence	Battles	R&V
	(1)	(2)	(3)	(4)
$ShockAg_{(t-1)}$	0.041***	-0.013**	0.001	0.043***
Standard error 200km, Time: 2 years	(0.011)	(0.007)	(0.008)	(0.010)
Standard errors 200km, Time: Infinite	(0.011)	(0.007)	(0.008)	(0.010)
Standard error 500km, Time: 2 years	(0.015)	(0.009)	(0.010)	(0.013)
Standard error 500km, Time: Infinite	(0.015)	(0.009)	(0.010)	(0.013)
Standard error 1000km, Time: 2 years	(0.016)	(0.010)	(0.011)	(0.014)
Standard error 1000km, Time: Infinite	(0.016)	(0.010)	(0.011)	(0.014)
$ShockExt_{(t-1)}$	0.018	-0.019	0.004	0.004
Standard error 200km, Time: 2 years	(0.016)	(0.012)	(0.015)	(0.014)
Standard errors 200km, Time: Infinite	(0.016)	(0.012)	(0.015)	(0.014)
Standard error 500km, Time: 2 years	(0.017)	(0.013)	(0.018)	(0.016)
Standard error 500km, Time: Infinite	(0.017)	(0.013)	(0.018)	(0.016)
Standard error 1000km, Time: 2 years	(0.017)	(0.013)	(0.018)	(0.017)
Standard error 1000km, Time: Infinite	(0.017)	(0.012)	(0.018)	(0.016)
$ShockMineral_{(t-1)}$	0.133***	-0.007	-0.019	0.143***
Standard error 200km, Time: 2 years	(0.034)	(0.013)	(0.019)	(0.033)
Standard errors 200km, Time: Infinite	(0.034)	(0.013)	(0.019)	(0.032)
Standard error 500km, Time: 2 years	(0.038)	(0.013)	(0.019)	(0.036)
Standard error 500km, Time: Infinite	(0.037)	(0.013)	(0.019)	(0.036)
Standard error 1000km, Time: 2 years	(0.038)	(0.014)	(0.019)	(0.038)
Standard error 1000km, Time: Infinite	(0.038)	(0.014)	(0.019)	(0.037)
$Excluded_{(t-1)}$	0.020***	0.005**	0.017***	0.013***
Standard error 200km, Time: 2 years	(0.005)	(0.003)	(0.004)	(0.004)
Standard errors 200km, Time: Infinite	(0.005)	(0.003)	(0.004)	(0.004)
Standard error 500km, Time: 2 years	(0.007)	(0.004)	(0.005)	(0.006)
Standard error 500km, Time: Infinite	(0.007)	(0.004)	(0.005)	(0.006)
Standard error 1000km, Time: 2 years	(0.008)	(0.004)	(0.006)	(0.007)
Standard error 1000km, Time: Infinite		(0.008)	(0.004)	(0.006)
(0.006)				
$Monopoly_{(t-1)}$	0.125***	0.027***	0.073***	0.088***
Standard error 200km, Time: 2 years	(0.019)	(0.005)	(0.014)	(0.015)
Standard errors 200km, Time: Infinite	(0.019)	(0.005)	(0.014)	(0.015)
Standard error 500km, Time: 2 years	(0.029)	(0.007)	(0.021)	(0.022)
Standard error 500km, Time: Infinite	(0.029)	(0.007)	(0.021)	(0.022)
Standard error 1000km, Time: 2 years	(0.038)	(0.009)	(0.028)	(0.028)
Standard error 1000km, Time: Infinite	(0.038)	(0.009)	(0.028)	(0.028)
CONTROL VARIABLES	YES	YES	YES	YES
CELL FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definitions of ACLED database (ACLED_INCIDENCE, ACLED_BATTLES and RIOTS AND VIOLENCE) and UCDP INCIDENCE. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation. p-values are reported in parentheses

*** p<0.01,** p<0.05, * p<0.1

Table C17: Alternative spatial temporal kernels standard errors. *Continuation*

VARIABLES	ACLED_incidence	UCDP incidence	Battles	R&V
	(1)	(2)	(3)	(4)
$ShockAg_{(t-1)} * excluded_{(t-1)}$	-0.032***	0.003	-0.006	-0.024***
Standard error 200km, Time: 2 years	(0.011)	(0.007)	(0.009)	(0.010)
Standard errors 200km, Time: Infinite	(0.011)	(0.007)	(0.009)	(0.010)
Standard error 500km, Time: 2 years	(0.015)	(0.009)	(0.011)	(0.013))
Standard error 500km, Time: Infinite	(0.015)	(0.009)	(0.011)	(0.013)
Standard error 1000km, Time: 2 years	(0.017)	(0.010)	(0.013)	(0.014)
Standard error 1000km, Time: Infinite	(0.017)	(0.010)	(0.013)	(0.014)
$ShockExt_{(t-1)} * excluded_{(t-1)}$	-0.037**	-0.002	-0.017	-0.035**
Standard error 200km, Time: 2 years	(0.020)	(0.014)	(0.019)	(0.019)
Standard errors 200km, Time: Infinite	(0.020)	(0.014)	(0.019)	(0.019)
Standard error 500km, Time: 2 years	(0.023)	(0.014)	(0.022)	(0.021)
Standard error 500km, Time: Infinite	(0.023)	(0.014)	(0.021)	(0.021)
Standard error 1000km, Time: 2 years	(0.025)	(0.014)	(0.023)	(0.022)
Standard error 1000km, Time: Infinite	(0.024)	(0.014)	(0.023)	(0.022)
$ShockMineral_{(t-1)} * excluded_{(t-1)}$	-0.072*	-0.017	0.007	-0.082**
Standard error 200km, Time: 2 years	(0.043)	(0.023)	(0.032)	(0.041)
Standard errors 200km, Time: Infinite	(0.044)	(0.023)	(0.031)	(0.042)
Standard error 500km, Time: 2 years	(0.046)	(0.024)	(0.032)	(0.044)
Standard error 500km, Time: Infinite	(0.047)	(0.024)	(0.032)	(0.044)
Standard error 1000km, Time: 2 years	(0.046)	(0.025)	(0.032)	(0.043)
Standard error 1000km, Time: Infinite	(0.047)	(0.024)	(0.031)	(0.044)
$ShockAg_{(t-1)} * monopoly_{(t-1)}$	-0.231***	-0.099***	-0.176***	-0.114***
Standard error 200km, Time: 2 years	(0.048)	(0.022)	(0.035)	(0.040)
Standard errors 200km, Time: Infinite	(0.049)	(0.022)	(0.035)	(0.040)
Standard error 500km, Time: 2 years	(0.067)	(0.026)	(0.046)	(0.050)
Standard error 500km, Time: Infinite	(0.067)	(0.027)	(0.046)	(0.050)
Standard error 1000km, Time: 2 years	(0.081)	(0.029)	(0.054)	(0.057)
Standard error 1000km, Time: Infinite	(0.081)	(0.029)	(0.054)	(0.057)
$ShockExt_{(t-1)} * monopoly_{(t-1)}$	-0.027	0.024**	0.022	-0.014
Standard error 200km, Time: 2 years	(0.027)	(0.013)	(0.020)	(0.025)
Standard errors 200km, Time: Infinite	(0.027)	(0.013)	(0.019)	(0.025)
Standard error 500km, Time: 2 years	(0.210)	(0.408)	(0.298)	(0.237)
Standard error 500km, Time: Infinite	(0.031)	(0.014)	(0.022)	(0.029)
Standard error 1000km, Time: 2 years	(0.035)	(0.014)	(0.024)	(0.032)
Standard error 1000km, Time: Infinite	(0.034)	(0.014)	(0.023)	(0.032)
$ShockMineral_{(t-1)} * monopoly_{(t-1)}$	-0.074	-0.533	0.056	-0.225
Standard error 200km, Time: 2 years		(0.196)	(0.390)	(0.284)
(0.226)				
Standard errors 200km, Time: Infinite	(0.199)	(0.395)	(0.283)	(0.233)
Standard error 500km, Time: 2 years	(0.210)	(0.408)	(0.298)	(0.237)
Standard error 500km, Time: Infinite	(0.213)	(0.413)	(0.298)	(0.243
Standard error 1000km, Time: 2 years	(0.218)	(0.415)	(0.306)	(0.242)
Standard error 1000km, Time: Infinite	(0.221)	(0.420)	(0.305)	(0.248)
CONTROL VARIABLES	YES	YES	YES	YES
CELL FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definitions of ACLED database (ACLED_INCIDENCE, ACLED_BATTLES and RIOTS AND VIOLENCE) and UCDP INCIDENCE. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation. p-values are reported in parentheses

*** p<0.01,** p<0.05, * p<0.1

Table C17: Alternative spatial temporal kernels standard errors. *Continuation*

VARIABLES	ACLED_incidence	UCDP incidence	Battles	R&V
	(1)	(2)	(3)	(4)
$ShockAg_{(t-1)} * EthnicPol$	-0.062***	-0.012	-0.016	-0.057***
Standard error 200km, Time: 2 years	(0.023)	(0.014)	(0.016)	(0.022)
Standard errors 200km, Time: Infinite	(0.023)	(0.014)	(0.016)	(0.022)
Standard error 500km, Time: 2 years	(0.025)	(0.014)	(0.017)	(0.023)
Standard error 500km, Time: Infinite		(0.025)	(0.014)	(0.017)
(0.024)				
Standard error 1000km, Time: 2 years	(0.028)	(0.015)	(0.018)	(0.026)
Standard error 1000km, Time: Infinite	(0.028)	(0.015)	(0.018)	(0.026)
$ShockExt_{(t-1)} * EthnicPol$	0.030	0.009	0.030	0.008
Standard error 200km, Time: 2 years	(0.040)	(0.030)	(0.033)	(0.038)
Standard errors 200km, Time: Infinite	(0.039)	(0.030)	(0.033)	(0.038)
Standard error 500km, Time: 2 years	(0.041)	(0.030)	(0.036)	(0.041)
Standard error 500km, Time: Infinite	(0.040)	(0.030)	(0.035)	(0.041)
Standard error 1000km, Time: 2 years	(0.040)	(0.029)	(0.036)	(0.043)
Standard error 1000km, Time: Infinite	(0.039)	(0.029)	(0.036)	(0.043)
$ShockMineral_{(t-1)} * EthnicPol$	-0.299**	-0.060	0.066	-0.347**
Standard error 200km, Time: 2 years	(0.134)	(0.073)	(0.067)	(0.137)
Standard errors 200km, Time: Infinite	(0.134)	(0.072)	(0.067)	(0.138)
Standard error 500km, Time: 2 years	(0.133)	(0.075)	(0.067)	(0.136)
Standard error 500km, Time: Infinite	(0.134)	(0.074)	(0.067)	(0.136)
Standard error 1000km, Time: 2 years	(0.133)	(0.076)	(0.065)	(0.135)
Standard error 1000km, Time: Infinite	(0.133)	(0.076)	(0.065)	(0.135)
CONTROL VARIABLES	YES	YES	YES	YES
CELL FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definitions of ACLED database (ACLED_INCIDENCE, ACLED_BATTLES and RIOTS AND VIOLENCE) and UCDP INCIDENCE. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation. p-values are reported in parentheses

*** p<0.01,** p<0.05, * p<0.1

Table C17: Alternative spatial temporal kernels standard errors. *Continuation*

VARIABLES	ACLED_incidence	UCDP incidence	Battles	R&V
	(1)	(2)	(3)	(4)
$ShockAg_{(t-1)} * EFractional$	0.073**	0.047**	0.034	0.068**
Standard error 200km, Time: 2 years	(0.035)	(0.023)	(0.025)	(0.033)
Standard errors 200km, Time: Infinite	(0.035)	(0.023)	(0.025)	(0.034)
Standard error 500km, Time: 2 years	(0.039)	(0.024)	(0.026)	(0.038)
Standard error 500km, Time: Infinite	(0.040)	(0.024)	(0.026)	(0.038)
Standard error 1000km, Time: 2 years	(0.045)	(0.025)	(0.027)	(0.042)
Standard error 1000km, Time: Infinite	(0.045)	(0.026)	(0.027)	(0.043)
$ShockExt_{(t-1)} * EFractional$	0.025	0.025	0.032	0.048
Standard error 200km, Time: 2 years	(0.037)	(0.023)	(0.026)	(0.038)
Standard errors 200km, Time: Infinite	(0.037)	(0.023)	(0.025)	(0.037)
Standard error 500km, Time: 2 years	(0.041)	(0.024)	(0.030)	(0.041)
Standard error 500km, Time: Infinite	(0.040)	(0.024)	(0.030)	(0.041)
Standard error 1000km, Time: 2 years	(0.043)	(0.024)	(0.032)	(0.044)
Standard error 1000km, Time: Infinite	(0.042)	(0.024)	(0.032)	(0.044)
$ShockMineral_{(t-1)} * EFractional$	0.327	0.083	-0.097	0.401*
Standard error 200km, Time: 2 years	(0.222)	(0.098)	(0.099)	(0.230)
Standard errors 200km, Time: Infinite	(0.222)	(0.097)	(0.097)	(0.231)
Standard error 500km, Time: 2 years	(0.222)	(0.099)	(0.100)	(0.230)
Standard error 500km, Time: Infinite	(0.222)	(0.097)	(0.099)	(0.231)
Standard error 1000km, Time: 2 years	(0.224)	(0.101)	(0.099)	(0.232)
Standard error 1000km, Time: Infinite	(0.225)	(0.099)	(0.097)	(0.234)
CONTROL VARIABLES	YES	YES	YES	YES
CELL FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definitions of ACLED database (ACLED_INCIDENCE, ACLED_BATTLES and RIOTS AND VIOLENCE) and UCDP INCIDENCE. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation. p-values are reported in parentheses

*** p<0.01,** p<0.05, * p<0.1

Table C17: Alternative spatial temporal kernels standard errors. *Continuation*

VARIABLES	ACLED_incidence	UCDP incidence	Battles	R&V
	(1)	(2)	(3)	(4)
$DroughtSEPI_{(t-1)}$	-0.005	-0.010	0.001	-0.001
Standard error 200km, Time: 2 years	(0.012)	(0.007)	(0.008)	(0.010)
Standard errors 200km, Time: Infinite	(0.012)	(0.007)	(0.008)	(0.010)
Standard error 500km, Time: 2 years	(0.014)	(0.010)	(0.010)	(0.012)
Standard error 500km, Time: Infinite	(0.014)	(0.009)	(0.010)	(0.012)
Standard error 1000km, Time: 2 years	(0.015)	(0.010)	(0.011)	(0.013)
Standard error 1000km, Time: Infinite	(0.015)	(0.010)	(0.011)	(0.013)
$DroughtSEPI_{(t-1)} * excluded_{(t-1)}$	0.013	0.022**	0.005	0.007
Standard error 200km, Time: 2 years	(0.015)	(0.011)	(0.012)	(0.014)
Standard errors 200km, Time: Infinite	(0.015)	(0.011)	(0.012)	(0.014)
Standard error 500km, Time: 2 years	(0.019)	(0.014)	(0.014)	(0.016)
Standard error 500km, Time: Infinite	(0.019)	(0.014)	(0.014)	(0.016)
Standard error 1000km, Time: 2 years	(0.020)	(0.014)	(0.014)	(0.017)
Standard error 1000km, Time: Infinite	(0.020)	(0.014)	(0.014)	(0.017)
$Mines_{(t-1)}$	0.006	0.016*	0.035***	-0.005
Standard error 200km, Time: 2 years	(0.014)	(0.010)	(0.011)	(0.013)
Standard errors 200km, Time: Infinite	(0.014)	(0.010)	(0.011)	(0.013)
Standard error 500km, Time: 2 years	(0.016)	(0.011)	(0.012)	(0.014)
Standard error 500km, Time: Infinite	(0.016)	(0.012)	(0.012)	(0.015)
Standard error 1000km, Time: 2 years	(0.016)	(0.012)	(0.012)	(0.015)
Standard error 1000km, Time: Infinite	(0.016)	(0.012)	(0.012)	(0.015)
$Mines_{(t-1)} * excluded_{(t-1)}$	0.018	0.009	0.012	0.005
Standard error 200km, Time: 2 years	(0.016)	(0.010)	(0.013)	(0.015)
Standard errors 200km, Time: Infinite	(0.016)	(0.010)	(0.013)	(0.016)
Standard error 500km, Time: 2 years	(0.017)	(0.012)	(0.013)	(0.016)
Standard error 500km, Time: Infinite	(0.017)	(0.012)	(0.014)	(0.016)
Standard error 1000km, Time: 2 years	(0.017)	(0.014)	(0.014)	(0.016)
Standard error 1000km, Time: Infinite	(0.017)	(0.014)	(0.014)	(0.017)
CONTROL VARIABLES	YES	YES	YES	YES
CELL FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definitions of ACLED database (ACLED_INCIDENCE, ACLED_BATTLES and RIOTS AND VIOLENCE) and UCDP INCIDENCE. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation. p-values are reported in parentheses

*** p<0.01,** p<0.05, * p<0.1

2.3.7 Shocks in neighbouring cells

Table C18: The effect of commodity prices and ethnic cleavages on conflicts: Robustness results.

Neighbouring cells.

VARIABLES	ACLED_incidence	UCDP incidence	ACLED battle	Riots and Violence
	(1)	(2)	(3)	(4)
$ShockAg_{(t-1)}$	0.041***	-0.014**	0.001	0.043***
	(0.009)	(0.005)	(0.007)	(0.009)
$ShockExt_{(t-1)}$	0.018	-0.019*	0.004	0.003
	(0.015)	(0.012)	(0.013)	(0.013)
$ShockMineral_{(t-1)}$	0.131***	-0.008	-0.020	0.141***
	(0.033)	(0.013)	(0.020)	(0.031)
$ShockAg_{(t-1)}(Neighbouring_cells)$	0.004	-0.005	-0.001	0.006
	(0.007)	(0.004)	(0.005)	(0.006)
$ShockExt_{(t-1)}(Neighbouring_cells)$	-0.006	0.006	-0.007	0.000
	(0.012)	(0.008)	(0.010)	(0.011)
$ShockMineral_{(t-1)}(Neighbouring_cells)$	-0.021	-0.016	-0.010	-0.021
	(0.021)	(0.011)	(0.014)	(0.020)
$Excluded_{(t-1)}$	0.020***	0.005**	0.017***	0.013***
	(0.004)	(0.002)	(0.003)	(0.003)
$Monopoly_{(t-1)}$	0.125***	0.027***	0.073***	0.088***
	(0.014)	(0.004)	(0.011)	(0.012)
$ShockAg_{(t-1)} * excluded_{(t-1)}$	-0.033***	0.003	-0.006	-0.025***
	(0.009)	(0.006)	(0.007)	(0.008)
$ShockExt_{(t-1)} * excluded_{(t-1)}$	-0.072*	-0.017	0.008	-0.081**
	(0.042)	(0.023)	(0.032)	(0.040)
$ShockMineral_{(t-1)} * excluded_{(t-1)}$	-0.072*	-0.017	0.008	-0.081**
	(0.042)	(0.023)	(0.032)	(0.040)
height$ShockAg_{(t-1)} * monopoly_{(t-1)}$	-0.233***	-0.099***	-0.176***	-0.115***
	(0.040)	(0.018)	(0.030)	(0.035)
$ShockExt_{(t-1)} * monopoly_{(t-1)}$	-0.027	0.025**	0.022	-0.014
	(0.023)	(0.012)	(0.017)	(0.021)
$ShockMineral_{(t-1)} * monopoly_{(t-1)}$	-0.066	-0.527	0.060	-0.217
	(0.178)	(0.358)	(0.263)	(0.211)
$ShockAg_{(t-1)} * EthnicPol$	-0.062***	-0.013	-0.016	-0.058***
	(0.022)	(0.013)	(0.016)	(0.020)
$ShockExt_{(t-1)} * EthnicPol$	0.027	0.027	0.033	0.051
	(0.033)	(0.022)	(0.023)	(0.033)
$ShockMineral_{(t-1)} * EthnicPol$	-0.298**	-0.060	0.067	-0.346**
	(0.133)	(0.069)	(0.066)	(0.138)
$ShockAg_{(t-1)} * EFractional$	0.073**	0.048**	0.034	0.068**
	(0.033)	(0.021)	(0.024)	(0.031)
$ShockExt_{(t-1)} * EFractional$	0.016	0.002	0.025	0.034
	(0.032)	(0.022)	(0.023)	(0.031)
$ShockMineral_{(t-1)} * EFractional$	0.325	0.084	-0.097	0.400*
	(0.221)	(0.095)	(0.096)	(0.230)
$Drought_{(t-1)}$	-0.005	-0.010*	0.001	-0.001
	(0.010)	(0.006)	(0.007)	(0.009)
$Drought_{(t-1)} * excluded_{(t-1)}$	0.013	0.023***	0.005	0.008
	(0.014)	(0.009)	(0.010)	(0.012)
$Mines_{(t-1)}$	0.006	0.016**	0.035***	-0.005
	(0.013)	(0.008)	(0.010)	(0.012)
$Mines_{(t-1)} * excluded_{(t-1)}$	0.019	0.010	0.013	0.005
	(0.015)	(0.009)	(0.012)	(0.014)
Observations	167254	196807	167254	167254
R-squared	0.007	0.006	0.007	0.007

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following for conflicts following the definition of ACLED incidence database (ACLED_INCIDENCE). LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 100km radius and for two periods of correlation. Cell, country and year fixed effects. Control variables. p-values are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1