The Role of Ethnic Characteristics in the Effect of Income Shocks on African Conflict

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1 Introduction

Conflict is among the most robust determinants of low economic growth and high mortality (see, e.g., Collier and Hoefler, 2004, and Hegre and Sambanis, 2006). It causes unemployment, human capital loses, reductions in income and displacements of the population, and is a leading cause of hunger and general food insecurity in several parts of the world. Therefore, understanding the determinants of conflict is an important objective that investigators have integrated into their research agendas.

Among those determinants, the impact of income on conflict has been widely studied in the literature.[1] Economists and political scientists have also emphasized the role of ethnic cleavages on the generation of violence.[2] However, much less attention has been devoted to the study of the role of ethnic status in the propagation of income shocks. This is an important gap, because ethnic marginalization and diversity may work as amplifiers of the perceived economic costs and benefits—through for example a sense of grievance—and also as means of filtering areas where governments might be stronger.

We fill this gap focusing on Africa, 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 were involved in conflicts. More specifically, we answer the following question. How do the diversity and political status of ethnic groups affect the impact of income shocks on conflict? We focus on shocks coming from agriculture, because of its importance in food security, and because the agricultural sector still employs more than 50% of the total labor force in Sub-Saharan Africa according to ILO (2019). 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, and consider different measures of ethnic status, namely, spatial polarization and fragmentation, and monopoly and excluded political power. Our approach exploits the arguably exogenous nature at the cell level of variations in income shocks related to international commodity prices and climate conditions.[3] To further preserve exogeneity, international prices are weighted at the cell level using information about crop suitability from the FAOs global agroecological zones (GAEZ) as in Berman and Couttenier (2015), and ethnic variables are measured before the start of the sample period.

Nevertheless, even though the effect of this interaction on conflict is still far from being well understood, it has already received some interest. Janus and Riera-Crichton (2015) analyze it, 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.[4] 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 suitability with information on the movement of global commodity prices, climate conditions, and the four different ethnic-status variables mentioned previously (fragmentation, polarization, excluded groups and monopoly groups). We also make a step forward by introducing the spatial ethnic fractionalization index developed at the cell level by Montalvo and Reynal-Querol (2017) and by adapting the spatial ethnic polarization index to the cell level.

Following the work of McGuirk and Burke (2020) (MB from now on), which also employs geocoded data, we differentiate between two sources of violence—factor conflict and output conflict—and between two types of locations—food-producing cells and food-consuming cells. Factor conflict is related to large-scale conflict such as battles over the control of territory and production means. Output conflict, in turn, is associated to smaller-scale conflict over the appropriation of surplus. Food prices in food-producing areas are captured through a producer price index, and in food-consuming cells through a consumer price index.

MB estimate a negative impact of food prices on factor conflict in food-producing cells but a positive one in food-consuming cells. As argued by MB, this opposing-effects result is difficult to reconcile with theories that emphasize a one-direction impact such as the state capacity mechanism or the rapacity effect, and provides evidence that the opportunity-costs channel, whose direction can vary depending on whether agents are producers or consumers, is a main source of conflict. They also find that food prices have a positive impact on output conflict in both food-producing and food-consuming areas, which gives also support to the opportunity cost mechanism.[5]

Our findings reinforce the ones obtained by MB but add new aspects and point out an important role of state-capacity (as in Bazzi and Blattman, 2014) and ethnic grievance as determinants of conflict. More specifically, results reproduce the ones obtained by MB for factor and output conflict even when ethnic heterogeneity is considered in the regression. Support for the state capacity channel, on the other hand, comes from the interactions of the agricultural-commodity income shocks with the ethnic diversity variables. The sign of the estimates is always positive across price indices and conflict definitions. That is, the effect of food-price shocks tends to be less negative (or more positive) in more ethnically fractionalized and polarized areas. The lack of opposing effects in food-producing and food-consuming areas on factor conflict makes the result inconsistent with the opportunity cost mechanism. Moreover, the necessary dominance of opportunity costs over the rapacity effect to get the MB results leads us to interpret this finding as pointing to an important role of state capacity, given that more fractionalized or polarized societies signal weaker states suffering more from social tensions (Esteban and Ray, 1999).

Additionally, our estimates imply that the effect of the interaction between food prices and political ethnic cleavages depends on the type of cell and conflict. In food-producing areas, the impact is negative with battles and with output conflict. In food-consuming areas is, on the other hand, positive with both types of violence as well. These results provide evidence and add a location dimension that supports the argument put forward by Roessler (2011) that excluded ethnic groups can have different effects depending on the type of conflict. He sustains that the gain in government's power (or state capacity) from the exclusion of certain groups may come at the cost of displacing the conflict from politics to society, due to the feeling of grievance induced on the excluded population. It could be argued that this trade-off shows in our estimates: in food-consumption cells, the grievance mechanism dominates, possibly exacerbating the perceived opportunity cost, and due to a larger capacity of excluded-group members to get organized in urban areas. In food-producing cells, on the contrary, the state capacity effect dominates at least in the output conflict regression; otherwise, the sign would have to be positive.

We also disaggregate the measure of output conflict, which is the one considered by MB, in its two components: riots and violence against civilians. Both measures are taken from the Armed Conflict Location and Event Data Project (ACLED). Riots represent violent events where rioters engage in disruptive acts. Violence against civilians, in turn, refers to an organized armed-group inducing violence upon unarmed civilians. Hence, violence against civilians is an intermediate type of conflict that lies between organized armed-group battles—which in the main analysis is taken from the Uppsala Conflict Data Program (UCDP) to proxy factor conflict—and riots. This distinction shows up clearly in our estimations. In particular, the response of violence against civilians to the income shocks shares with factor conflict more than twice the number of coefficient signs and significance than with riots. They share, for example, with one exception, all signs of the coefficients related to both producer and consumer prices, possibly signaling that in both cases conflict is exerted by organized armed groups. However, like riots and unlike factor conflict, violence against civilians responds positively to consumer prices in urban areas; thus, implying that this type of output conflict has an important urban component. It is also interesting that, unlike violence against civilians, riots respond much less to political ethnic heterogeneity.

Another interesting result from the disaggregation is that the estimated direct effect of food-prices on riots is negative; and although the coefficient is not significant in the main analysis, it becomes significant in some of the robustness tests, and the rest of robustness exercises retain the sign. This negative direct impact of food prices in food-consuming cells suggests an increase in state capacity to control insurgence, because the other two theories (i.e., opportunity cost and surplus predation) are not consistent with the estimated sign, and because the employed consumer price is a country-wide index that should reflect, at least in part, the capacity of local and central governments to raise revenues.

We consider droughts as another proxy for income shocks and estimate its effect jointly with food prices. The reason is that we expect that droughts capture variations in the quantity of local crop production much more closely than international prices. Following Harari and La Ferrara (2018) (HF from now on), we employ the SPEI Global Drought Monitor database that provides estimates of the potential evapotranspiration (PET). Without ethnic variables, the regression gives a positive impact of droughts on conflict. However, this direct effect tends to disappear once the political ethnic variables are included. In general, the qualitative results are the same than for producer prices, although as expected, with the opposite sign—notice that higher food prices and levels of droughts represent positive and negative income shocks, respectively. Our results are consistent with von Uexkull et al. (2016) who find, using georeferenced data, that droughts help sustain civil conflict battles, especially for agriculturally-dependent politically-excluded groups. We confirm their factor-conflict findings with our sample and methodology. In addition, when we look at the determinants of output conflict, the existence of excluded groups turns out insignificant for riots, whereas excluded and monopoly groups raise the marginal effect of droughts on violence against civilians.

The rest of the paper is organized as follows. Section 2 reviews the mechanisms proposed in the literature to justify a possible connection of income shocks and ethnicity with conflict. The data and the econometric methodology are presented in sections 3 and 4, respectively. Section 5 shows our main results. Several robustness checks of the results are conducted in section 6. Section 7 concludes.

2 Theories of Conflict

There exist several competing theories of the effect of income shocks on conflict. All of them are based on the economic insight that rational individuals weight the relative returns, costs, and risk for choosing between to produce or predate (Becker, 1968). One of them is the opportunity cost theory. Models of rebellion suggest that civilian's incentives to rebel rises as economic opportunities and household's real income decline (Grossman, 1991). As MB show, the effect can be positive or negative depending on the type of shock and conflict definition. If labor productivity (e.g., due to proper weather) or producer prices increase, real wages will go up and individuals will have less incentives to join armed groups. This predicted strong inverse relationship between commodity prices and conflict have been used in several papers such as Dal Bò and Dal Bò (2011). However, as MB argue, if consumer prices go up, the real wage of workers will go down, and individuals will have more incentives to fight.

A second theory, based on the state-is-a-prize mechanism suggests that rising prices should increase the risk of insurrection as a mechanism to capture rents or the surplus. This channel is also known as predatory behavior or the rapacity effect. It is especially relevant in the case of mineral and oil and gas that are many times controlled by the state. Nevertheless, as MB show, even though surplus predation can be also present in the case of agricultural income shocks in food-producing areas, its effect is dominated by the opportunity costs mechanism.

A third channel, the state capacity theory (see, e.g., Ross, 2012), states that rising rents provide the state with a stronger capacity to buy off the opposition, counter insurgents and strengthen control, and therefore, help prevent conflict. In addition, we argue that the state capacity effect does not need to show up only at the country level. All different layers of government—central, regional and municipal—have, many times, transferred revenue-collection and expenditure discretionary powers. Therefore, the capacity to buy off opponents and control rebellion and violence can vary between different cells that experience different shocks. Notice that predictions based on the state capacity mechanism are the opposite to the ones from the state-is-a-prize theory.

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. Conflict can be 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). Consequently, indexes of fractionalization and polarization as measures of diversity have been used in several empirical studies with the idea that ethnically diverse societies have a higher probability of ethnic conflicts (Collier and Hoeffler, 2004; Fearon and Laitin, 2003; Miguel et al, 2004). Whereas ethnic fractionalization measures the probability that two randomly selected individuals from a given location 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. Results using fractionalization indexes are surprisingly murky. However, papers like Montalvo and Reynal-Querol (2005) have found polarization as significant to explain the incidence of civil war.

Finally, political sciences have emphasized the potential importance of ethnic political diversity and political marginalization of ethnic groups in the incidence of conflict (Gurr, 1970; Horowitz, 1985; Baseadu and Pierskalla, 2014; Cederman et al., 2009, 2010, 2011; Wimmer et al. 2009). For example, Cederman et al. (2011) find the political inequality affects positively civil wars through grievance-based mechanisms.[6] Other authors argue that the effect may depend on the type of conflict and political inequality. Roessler (2011) argues that the exclusion of certain ethnic groups from politics increases the government's power, reducing the risk of a coup, but raises the threat of suffering a future ethnoregional rebellion. Baseadu and Pierskalla (2014), focusing on the interaction with the oil and gas endowment, hypothesize that ethnic exclusion should amplify the risk of conflict, while monopoly power of ethnic groups should cause the opposite effect through an state-capacity channel; they find evidence of the latter effect but not of the former.

In this paper, we consider both 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.[7] Few papers (e.g., Baseadu and Pierskalla, 2014; and von Uexkull et al., 2016) have used these variables in a grid-panel data context and never in conjunction with other measures of ethnic diversity.

Our key contribution is analyzing whether a plausible effect of ethnicity on conflict can be indirect. That is, we hypothesize that a positive income shock might have a different impact depending on the degree of ethnic diversity and the political status of ethnic groups. For example, a positive agricultural shock can decrease the probability of incidence of battles because of the opportunity cost mechanism. However, if trade among different ethnic groups involves monitoring costs because of the lack of trust between them, this opportunity cost effect will be weaker in cells with a higher degree of ethnic fragmentation. Another example, social tension that leads to weaker governments in more ethnically fractionalized or polarized societies can also cause a lower state capacity to benefit from positive income shocks. A third one, the presence of monopoly groups might exacerbate income inequality within the cell, thus reducing the opportunity cost of poor individuals, or alternatively allow the dominant tribe to more tightly control natural-resource rents that can provide the means to repress military threats or buy peace. Therefore, the type and degree of ethnic heterogeneity can affect the impact of income shocks on the probability of conflict, but the sign and magnitude of this effect is uncertain; it will depend on how ethnic characteristics alter the state capacity, state-as-a-prize and opportunity costs channels. We want to provide empirical evidence that help advance in this direction.

In sum, the main hypotheses that we want to test are the following. Three are related to the direct effect of income shocks: (i) if the opportunity cost channel dominates, positive income shocks reduce armed conflict in food-producing cells, but increase it in food-consuming areas; (ii) if the state-capacity mechanism dominates, positive income shocks decrease conflict in both food-producing and food-consuming locations; (iii) if, on the other hand, the rapacity effect predominates, positive income shocks rise conflict in both locations. The other three are related to the sensitivity of these effects to ethnic cleavages: (iv) ethnic fractionalization and polarization signal weaker states with less capacity to deliver the possible conflict-reducing effects of positive income shocks; (v) on the contrary, the existence of ethnic groups with monopoly political power signals stronger governments that enjoy stronger state capacity to get advantage of positive income shocks and reduce conflict; finally, (vi) more generally, political marginalization of ethnic groups (either monopoly or excluded) may increase the sense of grievance, thus raising the opportunity costs perceived.

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 km x 55 km at the equator).[8] 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 release, 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 conflict events. It also mitigates issues of potential measurement error in the geo-location of the data. The sample coverage of the conflict data goes from 1998 to 2013 across forty-nine African countries. In the rest of this section, definitions and sources for all variables employed in our regressions are given. The appendix provides this information in more detail, including several descriptive statistics tables (Tables A1 to A9) organized by variable, country, crop and natural resource. It also presents maps (Figures A2 to A6) that illustrate the different independent variables considered.

3.1 Conflict data

We use two different datasets containing the geo-location of conflict events in Africa: the Armed Conflict Location and Event Dataset or ACLED (Raleigh and Dowd, 2015); and the Uppsala Conflict Data Program Georeferenced Event dataset or UCDP-GED, version 5.0 (Sundberg and Melander, 2013; Croicu and Sundberg, 2016). Events are collected from various sources that include humanitarian agents, research publications, and local, regional or international press news. As will become evident, the use of different datasets 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 most cases) the precise day of the 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.[9] However, UCDP records events related to battles in consecutive years between an organized armed-group dyad only when they have caused at least 25 fatalities in at least one of those consecutive years. In this case, events are included for the entire period, that is, both for the years when such conflict crossed the 25 battle-related deaths threshold and for the years when it did not.

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. We will use as dependent variable three different ACLED aggregates: political violence in the form of (i) battles and (ii) violence against civilians; and protest events in the form of (iii) riots.

Given that factor conflict represents large-scale violence related with the permanent control of territory, MB argue that the appropriate measure is the UCDP-GED one, because it captures organized armed-force conflict. We later in the paper, for robustness, employ also ACLED battles as an alternative proxy. Output conflict, on the other side, captures conflict generated for the transitory appropriation of surplus. We are then targeting events that are less organized than large-scale battles. Therefore, and again following MB, output conflict will be measured using the ACLED categories riots and violence against civilians.

To create the measure of conflict incidence, we follow Berman et al. (2017) and MB and aggregate to the cell-year, coding with a value of 1 if cell c experienced a conflict during the year, and zero otherwise. In the robustness section, we also employ information on conflict intensity from the same sources.

3.2 Food-price indices

Our identification strategy is based on the use of income shocks related to agricultural commodities that can be considered exogenous at the cell level. We employ three proxies: an agricultural producer price (APP) index, a consumer price (CP) index, and a measure a droughts. The construction of the first two follow MB and employ international prices, and the construction of the third one follows HF and uses weather variables. Droughts are introduced in the regressions jointly with prices, because local climate conditions are more closely related to the quantity of production. Next we explain how we construct them.

To construct the agricultural-production price shocks, we combine time-series data on international commodity prices from the International Monetary Fund (IMF), the International Finance Statistics and the World Bank Global Economic Monitor with cell-specific time-invariant data of crops suitability and potential production from the FAO's Global Agro-Ecological Zones (GAEZ) dataset.[10] GAEZ provides crop potential production data constructed using location characteristics such as soil properties and climate conditions (temperature and rainfall), considering the average climate during the baseline period 1961-1990. This information is combined with crops growing requirements to generate a global GIS raster on the potential suitability of a cell for each crop potential production. A cell is considered suitable for crop production if it could achieve at least 40% of its maximum capacity. For each cell, these data can be used to have exogenous weights for agricultural-commodity prices, because the weights are not based on actual levels of production and consumption. In addition, we take the potential capacity in years before the starting date of our database sample. GAEZ produces spatial detail at the 0.0833 decimal degree, which we aggregate to our 0.5 degree cell level.[11]

We cover the following crops: banana, barley, cocoa, coffee, coconut oil, groundnuts, maize, oranges, oil palm, olive oil, rice, soybeans, sugar cane, sunflower, tea, tobacco and wheat. The next step is aggregating the monthly international commodity prices to an annual price series for each commodity, normalized to 1 in year 1990 (Fjelde, 2015; and Bruner and Ciccone, 2010). At each date t, the APP index in cell i at time t (APP_{it}) is the average across the $j = 1, .., n$ agricultural commodities of the international crop prices (P^A_{jt}) weighted by the time-invariant potential production shares (w_{ij}) of suitable crops; that is,

$$APP_{it} = \sum_{j=1}^{n} w_{ij} P^A_{jt}. \tag{1}$$

Our consumer price index is built using country-level data on food consumption patterns from the FAO Balance Sheets following the methodology in MB. The measure of food consumption is the calories per person-day available for human consumption from each primary commodity. Data on food supply are calculated combining statistics of production, imports and stock changes, corrected to eliminate the fed to livestock, the use of seeds, and losses during storage and transportation.[12] The resulting time-invariant consumption shares represent averages over the period 1990-2013. The reason for taking average shares is minimizing data issues based on gaps in the quality of the consumption series across countries and time.[13]

From the consumption side, the aggregation of prices is performed in a similar way as for the APP Index, although using the same time-invariant crop shares for all the cells that belong to the same country. The time variability of our index is given by the vector of commodity prices P_{jt}^{A}. In particular, the CP index in year t and a cell i that belongs to country c is given by:

$$CP_{ct} = \sum_{j=1}^{n} \kappa_{jc} P_{jt}^{A}; \tag{2}$$

where κ_{jc} represents the crop share of calories per day and person in country c; and crops $j = 1, ...n$ are contained in the set of primary commodities consumed for which international prices exist. Most of the important staple food, like maize, sorghum and wheat, are included in the index, along with more processed commodities such as sugar cane, oil olive and palm oil. All together, these products represent a big proportion of the calorie intake consumed by people in Africa.

3.3 Climate variables

We complete agricultural income shocks considering a measure of droughts, given the dependence of agriculture on weather conditions. Following von Uexkull et al. (2016) and HF, we focus on a crop-specific climate shock, the drought SPEI Growing Season, which captures low SPEI episodes occurring during the growing season of the main crop in a given cell.[14] Specifically, the variable gives the proportion of months in the growing season that are part of the longest streak of consecutive months in that growing season with SPEI-I values below -1.5.[15] Thus, higher values of this variable means low levels of SPEI in the growing season in consecutive months, that is, a higher incidence of drought.

More specifically, the index uses annual numbers from the SPEI Global Drought Monitor on drought conditions, combining both temperature and rainfall data during the growing season calendars of the main crop cultivated in each cell. We use this measure of droughts because precipitation might not be an accurate measure of climate variation impacting agriculture. We look at the impact of climatology during the crop growing season, in turn, because is then when crops are more sensitive to adverse climate conditions, and hence, affect more intensively farms' future agricultural income and food availability. Robustness checks are conducted also for the climate variable adding the annual average SPEI.

3.4 Spatial ethnic diversity and political status

Our next task is describing the construction of the four different ethnic diversity measures: ethnolinguistic fractionalization, polarization, monopoly groups, and excluded groups. Their values in the regressions are maintained constant at their 1997 level, that is, one year before the starting point of the conflict data to mitigate possible endogeneity issues. We follow Montalvo and Reynal-Querol (2017) to compute the spatial ethnolinguistic fractionalization index (EF). Firstly, we use Vogt et al. (2015) that codes the settlement patterns of politically relevant ethnic groups in independent states based on the group list in the Geo-referencing Ethnic Power Relation (GeoEPR) 2014 database. Matching our grid structure and the regional and statewide ethnic groups patterns for the year 1997, we estimate the share of the territory settled by a specific ethnic group. In particular, the index in cell i takes the form:

$$\mathrm{EF}_i = 1\text{-}\textstyle\sum_{j=1}^{N} \pi_j^2 = \sum_{j=1}^{N} \pi_j(1-\pi_j); \tag{3}$$

where π is the proportion of area that belongs to ethnic group j (for $j = 1, ..., N$).[16]

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

$$\mathrm{EP}_i = 4\textstyle\sum_{j=1}^{N} \pi_j^2(1-\pi_j). \tag{4}$$

These two ethnic diversity measures are bounded below by zero and above by one, but 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 just two, equally large groups.

Moving now to the spatial political ethnic diversity proxies, we control for both excluded and monopoly groups reflecting these political statuses. Excluded groups is based on the numbers directly supply by PRIO-GRID 2.0. Specifically, the excluded-group variable counts the number of excluded groups (discriminated or powerless) in a particular cell. The monopoly group proxy feeds from the Ethnic Power Relations (EPR) Dataset Core 2014. It is a dummy variable coded as 1 if there is at least a monopoly group in cell i, 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 EPR 2014 data.[17]

3.5 Socioeconomic variables

We complete our model using time-varying controls for socioeconomic characteristics that could affect conflict, directly or indirectly, and that could be argued to be relatively exogenous. In order to control for local economic activity, we introduce commodity price indices for oils and gas and mines. In particular, the construction of the local commodity price index for oil and gas uses geocoded data of the localization of oil and gas fields in Africa from PRIO-GRID v.1.2. This information is employed to build a time-invariant dummy variable (e_{ij}) coded as 1 if oil ($j = 1$) or gas ($j = 2$) or oil and gas (($j = 3$)) are present in a cell at any time during the period 1990-2013. Finally, we combine the dummy with the IMF data on world oil and gas annual prices to estimate a price index for cell i and time t (PI^E_{jt}) as follows:

$$PI^E_{it} = \sum_{j=1}^{3} e_{ij} P^E_{jt}; \tag{5}$$

where e_{ci} is a gas or/and oil dummy variable for cell i; and P^E_{it} is the annual price 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 (PI^M_{ct}). We use the information from the Mineral Resources Data System provided by the United States Geological Survey. Following Berman et al. (2017), we define a mineral-specific dummy variable coded as 1 in cells where at least one mine has been registered as active in the period 1990-2013 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. We combine the time-invariant dummies with price series from the IMF and the Global Economic Monitor (GEM) Commodities dataset, provided by the World Bank (WB), as follows:

$$PI_{it}^{M} = \sum_{j=1}^{n} m_{ij} P_{jt}^{M}; \tag{6}$$

where m_{ij} is the dummy variable of mineral-j mine-presence in cell i; and P_{jt}^{M} is the annual price for minerals produced in the mine j normalized to 1 in the year 1990. If we have more than one mineral mine-presence, m_{ij} equals 1 divided by the number of mines in the cell.

Finally, we consider the variable urban area to test the impact of the CI index in more urbanized cells. Our variable urban is the percentage of the surface in each cell covered by urban area. It is based on land use data from the Integrated Science Assessment Model-Historical Database of the Global Environment (ISAM-HYDE).

4 Empirical Methodology

As we mentioned previously, the aim of the paper is to study the sensitivity of the effect of agricultural-commodity income shocks on the likelihood of conflict to ethnic diversity and political status. In order to achieve this goal, we build on MB and propose a fixed-effect framework that takes the form:

$$Conflict_{ict} = D_i + T_{ct} + \sum_{k=0}^{2} ACIP_{ict-k}\beta_{t-k} + \sum_{j \in J} \sum_{k=0}^{2} (EC_{ic}^{j} * ACIP_{ict-k})\gamma_{t-k}^{j} + \sum_{k=0}^{2} Z_{ict-k}\delta_{t-k} + \varepsilon_{ict}.$$

(7)

This general estimation equation for conflict serves to explain all the different versions employed in our regression. In the main estimations, $Conflict_{ict}$ is a binary variable that takes on one if there have been conflict incidents in cell i, at country c and time period t and zero otherwise.[18] When the outcome variable wants to capture factor conflict, it will represent armed-force incidence from the UCDP-GED dataset in the benchmark estimation, and later for robustness we will use battles from ACLED and conflict intensity from UCDP-GED.[19] If, on the other hand, the dependent variable proxies output conflict, it will consist of the category social unrest from ACLED or its components riots and violence against civilians.

The variable D_i is a cell fixed-effect dummy. The term T_{ct} controls for time effects and can take two different formats. When the country-wide CP index is not included in the regression, $T_{c,t}$ corresponds to a set of country-year fixed effect dummies. However, when the three income-shock proxies are present, the country-year dummies would subsume the effect of the CP index, and consequently, to avoid this problem, T_{ct} is formed by two components—an year fixed effect dummy and a country-specific time trend. Because shock variables could be correlated with other cell-specific characteristics such as economic activity, our benchmark specification incorporates the matrix Z_{ict}, a set of control variables that include the oil-and-gas price index and the mineral-commodity price index described in the previous subsection. Later, this control matrix is expanded to consider the fraction of urban area and its interaction with the CP index.[20]

The variable ε_{ict} is the disturbance term. Because the shocks and the conflict measures can be clustered in time and space, we allow for serial and spacial correlation applying the method developed by Conley (1999) and Hsiang et al. (2011).[21] More specifically, the coefficients' standard errors are estimated employing a spatial heteroscedasticity and autocorrelation consistent (HAC) covariance matrix that allows for both location-specific 5-year-lag serial correlation and cross-sectional spatial correlation in a radius of 110 km. Following Berman et al. (2017), later we test the robustness of our results to spatial kernels from 55 to 1000 km, and serial correlations from 2 lags to assuming a temporal decay for the Newey-West/Bartlett kernel so slow that makes the serial correlation vanish in an infinite amount of (i.e. 100,000) years.

Moving now to our main variables of interest. The agricultural-commodity income proxy matrix $ACIP_{ict}$ can include, depending on the version, the APP index, the SPEI index for droughts, and the CP index. Because 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 (see, e.g., MB) the climate variable is always present in our regressions. These price and weather variables are incorporated over three consecutive years—the current period and two lags—to take into account possible effects of past shocks. We do the same for the control set Z_{ict}. Later in the paper we check results considering up to five lags. All price indices are introduced in the regression taking logs as in Berman et al. (2017).

The set J provides indices for each of the four ethnic characteristics considered in the paper. In particular, the different ethnic variables EC_{ic}^{j} are the following: the excluded group, the monopoly group dummy, ethnolinguistic fractionalization, and ethnic polarization. Notice that in the regression the ethnic variables are time invariant—we assign pre-sample values of the ethnic characteristic to all periods in order to mitigate endogeneity concerns. Because of this, we exclusively focus on the interactions with the income shock variables, and do not include in the estimation model their independent effects, as they are captured by the cell fixed-effect dummies.

Finally, the vectors β_t, γ_t^j and δ_t are composed of the coefficients that we want to estimate. The βs capture the direct impact on conflict of the exogenous income shocks, and the γs provide the effect of their interactions with the ethnic variables. Equation (7) is estimated as a fixed effect linear probability model (LPM). We prefer this estimator to alternative frameworks for binary dependent variables such as the probit or the logit because it allows for a clear interpretation of the coefficients. The estimated coefficient measures the change in the probability of conflict incidence if, *ceteris paribus*, the explanatory variable of interest increases in one unit. Nevertheless, in the robustness section, we also perform estimation employing a conditional fixed-effect logit.

5 Results

Our next task is presenting the estimation results. In all cases, the conflict variable is a binary measure of incidence. The tables (all of them located in the appendix) report, for each independent variable, the sum of the contemporaneous and lagged effects and the corresponding Conley (1999) standard error.[22] First, we describe the findings when the dependent variable is factor conflict (results are presented in Table A10 and Figure 1). Second, we search for the determinants of output conflict measured as a compound of riots and violence against civilians (Table A11 and Figure 2). Third, we analyze the determinants of each of the two components of output conflict separately (Tables A12 and A13 and Figures 2 and 4). Fourth, we test for the role of urban area on the effect of consumer prices (Table A14 and Figure 5). Finally, we interpret the results in light of the existing theories. The robustness tests are relegated to Section 6.

The structure of Tables A10 to A13 is the same. All regressions include cell dummies, and the oil-and-gas and the mineral price indices as control variables. Column (1) provides results when only the APP and the drought indices are considered as variables of interest; in this case, as mentioned previously, country-year fixed effects are controlled for. Column (2) shows the results when the CP index is added to the other two agricultural-commodity income-shock indices; now temporal effects are captured by year dummies and country-specific trends. These first two columns are included for comparison to previous literature. Columns (3) to (12) search for the sensitivity of the income-shock effects to ethnic heterogeneity. Columns (3) and (4) add only the interaction with political ethnic variables to the regressors considered by columns (1) and (2), respectively. Similarly, columns (5) and (6) expand the regressions in columns (1) and (2) incorporating only ethnolinguistic fractionalization, and columns (7) and (8) incorporating only ethnic polarization. Ethnolinguistic fractionalization and ethnic polarization are never jointly considered in the regressions because of the severe multicollinearity problem that this brings—the correlation between the two variables in our sample is 0.98. The last four columns consider how estimated coefficients and consistent standard errors in columns (1) and (2) change when the political and diversity ethnic measures are included together. In particular, columns (9) and (10) add excluded-groups, monopoly groups and fractionalization, and columns (11) and (12) add excluded-groups, monopoly groups and polarization. The bottom part of the tables provides the unconditional probability of the conflict variable for the sample employed in each column.

Looking at the tables, it is immediate that results with fractionalization are almost identical to the ones with polarization and quantitatively very similar.[23] This high similarity occurs in all regressions estimated in this paper, due to the high correlation between the two ethnic diversity variables in our sample. The main difference between including one ethnic diversity variable or the other is just the precision of the estimated coefficients. In general, the coefficients of variables that contain polarization show significantly narrower confident intervals that the corresponding ones that include fractionalization. Given this, we will comment exclusively on the results obtained with polarization.

Moving now to the figures, Figures 1 to 4 share the same structure as well. Each figure consists of nine charts split in three columns of three charts. They are constructed employing the estimated coefficients and standard errors provided by our preferred regression, column (12) in the tables, which represents the most complete model with polarization.[24] The goal is to show the sensitivity of the income-shock effects to the different ethnic measures separately. The first column of charts provides the estimated marginal effect on conflict and its 90% confidence interval of a one unit increase in the log of the APP index, as a function of the number of excluded groups (first row), whether there is or not a monopoly group (second row) and the degree of polarization (third row), assuming that the other ethnic characteristics take on zero. The second and third columns of charts give the same information but focusing on the drought index and the log of the CP index, respectively.

5.1 Factor conflict

We start by presenting in Table A10 and Figure 1 results when in regression (7) the dependent variable signals whether there have been large-scale organized-armed-group conflict events according to UCDP-GED. We can see that without ethnic variables columns (1) and (2) in Table A10 reproduce the qualitative findings obtained by MB and HF. As in MB, the coefficient for the APP index is negative and significant with both time-effect formats, and the CP index is positive and significant. Additionally, as in HF, the coefficient for droughts is positive and significant in both columns.[25]

[INSERT FIGURE 1 AROUND HERE]

Feeding on the results in column (12) of Table A10, Figure 1 displays the sensitivity of the income-shock effects to ethnic cleavages. Notice that the estimated values and confidence intervals when the ethnic variables take on zero give the direct impact of the income shocks and its significance. We can see that the APP and CP indices show significant direct effects, the former with a negative value and the latter with a positive coefficient, as in MB. The largest amplification effects are associated to the presence of excluded groups, and its interaction is significant with APP and with droughts (see Table A10).[26] For example, compared to cells without them, locations with two (five) excluded groups multiply the negative effect of APP shocks on the risk of factor conflict by 4.8 (10.6) times. This number for drought shocks is 20.0 (48.5) times.

The second row of charts imply that the presence of monopoly groups is important for the transmission of a producer price shock. In particular, its negative impact is 7.4 times larger when these groups exist. The existence of monopoly groups also multiply the positive effect of the CP shocks by 1.7 times. This difference in the case of consumer prices and droughts is not significant.

The role of polarization (third row) is the weakest. In Figure 1 , differences across ethic diversity levels in the marginal impact of the shocks are only significant in the case of APP. In particular, a sufficiently large degree of ethnic polarization makes the estimated effect of changes in producer prices become positive. Looking now at Table A10, it is interesting to notice as well that the interaction between consumer prices and polarization is positive and close to showing significance; later when we introduce urban area, it will do so.

To further quantify the results, we again concentrate on column (12) of Table A10 and measure, following a standard procedure in the literature, what we call from now on the "implied total impact". More specifically, we look at the effect, in percentage points, of a one standard deviation change in an income proxy on the probability of conflict when all the ethnic variables take on their average value.[27] The impact measure, therefore, tells us the estimated change in the probability of conflict incidence in the average cell.

The implied total impact of the APP index equals -5.33. That is, a one standard deviation decrease in the log of the APP index raises the probability of armed conflict in the average cell by 5.33 percentage points; with the direct effect and the interaction with excluded groups contributing each of them about half of the impact. The interaction of producer prices with monopoly groups also decreases the probability of conflict by 1.06 percentage points, but this effect is almost exactly offset by ethnic diversity. The implied total impact of droughts is 0.23, due almost fully to the significant increase in the risk of conflict caused in cells with excluded groups. Finally, the implied total impact of consumer prices is 1.36. Looking at the details, the risk of battles in the average cell significantly increases by the direct impact of the CP index and its interaction with monopoly by 1.28 and 0.05 percentage points, respectively. Hence, the strongest estimated effect is the one of producer prices and the smallest the one of droughts.

5.2 Output conflict

Next, we look at the determinants of output conflict, measured as events where riots and violence against civilians occur. Table A11 and Figure 2 present our findings with the ACLED incidence as the dependent variable. In columns (1) and (2) of Table A11, all the estimated coefficients are positive and, with the exception of the CP index, strongly statistically significant. These results are consistent with MB and HF.[28]

[INSERT FIGURE 2 AROUND HERE]

Figure 2 tells us that, compared to the regressions without ethnic variables, the direct effects maintain the signs, but only the drought index remains significant. It also conveys the message that, for output conflict, the existence of monopoly ethnic groups is the most important amplifier. Monopoly groups change the sign of the effect of an APP shock to negative and increase its impact by 32.0 times in absolute value. They also multiply the effect of consumer prices by 4.0. The difference in the case of droughts is not significant.

Excluded groups are, in turn, only significant for changes in consumer prices (see Table A11). The estimated marginal effect of the CP index experiences a 2-fold (3.5-fold) increase when the number of excluded groups goes up from zero to two (five). Finally, the sensitivity to polarization is only significant for the effect of producer prices. A fully polarized society experiences a positive effect of producer prices on output conflict that is 6.8 times larger than a society with zero polarization.

Quantitatively, employing the estimates in column (12) of Table A11, the implied total impact of a one-standard-deviation increase in the APP index is -0.41 percentage points, much lower than in the case of factor conflict, with monopoly groups and ethnic polarization accounting for -1.44 and 2.29 percentage points, respectively. The implied total impact of droughts equals 0.33 percentage points, and the only (weakly) significant contribution of 0.23 is generated by the direct effect. Lastly, the total impact of the CP index on output conflict is 1.38, mainly as a consequence of its direct effect (0.94), which is close to being significant, amplified by the presence to politically excluded groups (0.23) and monopoly groups (0.17).

Our estimates imply as well that the importance of ethnic cleavages in the risk of conflict depends on the type of shock and conflict definition. If we look at the sum of the absolute values of the different components of the implied total impact, the APP-index direct effect amounts to 36.34% of the total for factor conflict and 17.30% in the output conflict case. These figures for droughts are 16.45% and 50.56%, and for the CP index, 94.52% and 67.70%. Hence, looking at the sensitivity to ethnic heterogeneity, it is much higher for producer prices and droughts than consumer prices, and droughts provides the largest one in factor conflict, whereas producer prices gives the biggest in output conflict.

5.3 Riots versus violence against civilians

We now disaggregate output conflict in its two components. This is important because the ACLED category "violence against civilians" could be considered an intermediate case of violence. Unlike the one-sided violence recorded in UCDP, ACLED considers all events, independently of the number of casualties; and then, it can be considered a small-scale conflict measure. However, as the one-sided violence recorded in UCDP, ACLED violence against civilians represents violence carried out by organized armed groups. As will become evident in a moment, both subcategories respond differently to income shocks and ethnic characteristics. The results with riots are closer to the original MB's output conflict findings, whereas the determinants of violence against civilians are closer to the ones of factor conflict.

Tables A12 and A13 and Figures 3 and 4 present the estimation results based on this disaggregation. Looking at the findings for riots in Figure 3 and Table A12, the direct effects of the APP index and droughts are positive and significant. Conversely, the one of the CP index is not. The effect of excluded groups is statistically non-important; whereas the one of monopoly groups matters for the impact of APP and CP shocks, although not for droughts. In particular, monopoly groups flip the sign of the effect of changes in both price indices. In turn, the significant interactions of polarization with droughts and the CP index tend to offset their direct effects.

[INSERT FIGURE 3 AROUND HERE]

Column (12) of Table A12 implies a total impact of a one-standard-deviation rise in the APP index on the likelihood of riots of +5.11 percentage points; this is a consequence of its direct effect (6.86 percentage points) and the interaction with monopoly (-0.61). In turn, the implied total impact of droughts is 0.15 percentage points, and only its direct contribution and the one of its interaction with polarization are significant and equal to 0.28 and -0.12, respectively. Finally, the total impact of the CP index is -0.30 percentage points; as a consequence mainly of its direct effect, partially offset by the incidence of the ethnic variables. The largest impact is then again the one of producer prices.

In Figure 4 and Table A13, we can see that, unlike in the case of riots, the direct effect of producer prices on violence against civilians is negative, the one of consumer prices is positive, and the one of droughts is insignificant. Also unlike in the case of riots, excluded groups play an important role as transmission channel for droughts and CP shocks. For example, the presence of two (five) excluded groups multiplies the effect of the droughts and CP indices on violence by -3.6 and 2.0 (-10.6 and 3.5), respectively. Monopoly groups also play a larger role, and become important for the three types of income shocks. When monopoly ethnic groups are present, the effects of APP, droughts and CP on violence against civilians are 11.1, -13.6 and 3.5 times larger, respectively. Contrary to the case of riots, ethnic polarization in the case of violence only matters for APP shocks, making their effect go from negative to positive if ethnic diversity is sufficiently large.

[INSERT FIGURE 4 AROUND HERE]

In terms of the implied total impact, column (12) of Table A13 delivers that the one of the APP index represents a decrease in the risk of violence of 3.12 percentage points: its direct effect contributes -2.87; and there are opposite indirect effects of politically-marginalized groups and ethnically diverse societies. The implied total impact of droughts and its components are the smallest among the three types of shocks and are always less than or equal to 0.20 percentage points. The total impact of a one-standard-deviation increase in consumer prices, in turn, equals 1.62 percentage points, with a direct effect of 1.20, and an amplifying effect of political ethnic variables of 0.47.

Comparing the importance of ethnic cleavages in riots and in violence against civilians, the direct effect in the case of riots represents 79.67%, 68.89% and 71.13% of the sum of all (direct and interaction) effects in absolute values for the APP index, droughts and the CP index, respectively. Thus meaning that ethnic differences are relatively less important. However, in the case of violence against civilians, the corresponding direct effects are 38.11%, 31.18% and 69.80% of the impact sum; that is, for producer-price and drought shocks, the sensitivity to ethnic cleavages is key. This, again, makes violence against civilians closer to factor conflict than to riots.

5.4 Consumer prices and urban area

We have not found MB's positive direct effect on riots of food-price increases in food-consuming cells. However, consumer prices for food should be relatively more important in urban areas, where the weight of the agricultural sector on total employment is significantly lower. Consequently, the last set of results that we present in this section correspond to the scenario in which the fraction of urban area and its interaction with the CP index are included in the estimation model.

Table A14 and Figure 5 display the findings. Table A14 has a different format than the previous ones. Columns (1) to (4), (5) to (8), and (9) to (12) give results when the dependent variable is UCDP conflicts, riots and violence against civilians, respectively. Figure 5, in turn, shows the marginal effect of the three shocks for different fractions of urban area in the cell. We deduce from the figure that the the sensitivity of the effect of CP shocks on riots (second chart) and violence against civilians (third chart) is positive and strongly significant, whereas the one of factor conflict (first chart) is insignificant. Thus confirming that, in urban areas, consumer prices do increase the probability of output conflict as predicted by the opportunity cost mechanism.[29] In addition, looking at Table A14, the urban area fraction shows up as negative and significant for both output conflict variables.

[INSERT FIGURE 5 AROUND HERE]

Regarding the other regressors, most qualitative effects of the income shocks and the ethnic variables remain more or less unchanged for all outcome variables. The only remarkable changes are the following: in the factor conflict regression, the interaction of consumer prices and polarization becomes positive and significant; and in the case of riots, political ethnic variables lose power and only the interaction of the CP index with monopoly groups remains significant.

In terms of the magnitudes, the implied total impacts only experience a significant change in the case of both price indices for riots and the APP index for violence against civilians. In particular, taking the estimates of column (8), the total impact of the CP index in the riots regression goes up from -0.30 to 0.05 percentage points due to its interaction with urban areas, and the impact of the producer price goes down from 5.11 to 4.35 due to the weaker positive direct effect. Moving now to column (12), the implied total impact of the APP index goes from -3.79 to -4.59 in the violence regression, because of the stronger negative direct effect of producer prices. Consequently, the fraction of the total effect explained by the sensitivity to ethnic cleavages goes down in some of these cases. Nevertheless, for the APP index in violence against civilians this sensitivity still explains 55% of the total.

5.5 Theories behind the results

Our results in the main analysis sections reinforce the economic mechanisms emphasized by MB, but at the same time, add new aspects and point out a greater role of grievance and state capacity as determinants of conflict. One difference is that we find that the ACLED category violence against civilians has more determinants in common with factor conflict than with riots. Therefore, differentiating between organized and non-organized conflict can be more informative than between factor and output conflict.

To start with, producer prices in our sample have a negative effect on conflict that involves any type of organized armed groups, namely, the UCDP evens and the ACLED violence against civilians. This is also found by MB but only with the UCDP data. Nonetheless, the interpretation suggested by MB is still valid. That is, the result suggests an important role of the opportunity cost of becoming a soldier: in food-producing areas, increases in food prices raise the real value of salaries and generate opportunity-cost incentives for workers not to join armies engaged in organized violence. We also find, as MB, a positive effect of consumer-price shocks on organized-group conflict (but not on riots). Therefore, the decrease in real wages caused by food-prices in food-consuming areas leads more workers to become organized fighters through an opportunity cost mechanism.

Droughts play a weaker role with all conflict definitions. We have defended that international prices and local climate conditions should proxy different aspects of agricultural income. Nevertheless, it cannot be fully discarded that prices at a certain extent capture the effect of droughts. Focusing on the direct effect, droughts during the growing season have a clear positive impact on riots. This effect has been already found by previous literature, like Almer et al. (2017). An opportunity costs mechanism is again more likely behind this result. As water, an important input of production, becomes scarcer, the productivity of land falls and the incentives to riot in favor of the appropriation of surplus increase.

The existence of politically excluded and monopoly groups reinforces also this channel for organized armed-group conflict and, unlike in Baseadu and Pierskalla (2014), amplify the risk of conflict in the same direction. More specifically, excluded and monopoly groups push the effect of an increase in the APP index or a decline in droughts towards a negative sign, and the one of a rise in consumer prices towards a positive sign. Given that increases in producer prices and less intense droughts can be seen both as positive income shocks that lead to higher real wages of farmers, the direction of their effect can be interpreted using the same theories. In particular, these results can be interpreted as an outcome of opportunity costs.[30] A lower degree of ethnic confrontation in government due to the exclusion or monopoly of certain groups can increase the sense of grievance, and therefore, the politically-harmed groups can become more sensitive to variations in the opportunity costs described in the previous paragraph that make food prices affect organized violence in opposite directions in food-producing and food-consuming areas. Notice that these opposing effects can be generated neither by the rapacity effect theory nor by the state capacity channel.

By the same token, the stronger positive response of organized armed-force conflict to both producer-price and consumer-price shocks that we find in more polarized societies when urban area is considered is not consistent with the opportunity cost effect. It cannot be either a consequence of a stronger predatory behavior in those areas, since as MB argues the opportunity cost effect dominates rapacity in the response of factor conflict to producer-price shocks. Hence, this positive response of conflict must be a consequence of state capacity; that is, a larger degree of ethnic diversity signals weaker states suffering more from social tensions (Esteban and Ray, 1999) that are able to benefit less from the violence-reducing opportunities offered by positive income shocks.

The generation of riots is also affected by the opportunity cost and state capacity mechanisms but not in same way than factor conflict. The role of producer prices is now the opposite than in organized violence, it is positive. As MB shows, this can be caused by a combination of the opportunity-cost and predatory effects. To fully understand this, let us briefly explain how the MB theoretical model works. Output conflict arises if the individual reallocates effort from the production activity to the appropriation of surplus. Prices in their model can be associated to three types of goods: agricultural-commodities produced in the cell but exported to other cells; food-items produced and consumed within the same cell; and crops imported from other cells for consumption. The first two affect the producer-price index and the last two the consumer-price index. Consequently, when the cell's producer price goes up, this increase is larger than the rise in the cell's consumer price, because some commodities are imported. Therefore, the real (consumer-price-deflated) value of the cell's production rises if these food-items are exported, but the real wage falls if the produced food is for within-cell consumption. The former triggers a rapacity effect, whereas the latter describes an opportunity cost channel. Both of these effects make output conflict increase, that is, generate additional allocation of effort to steal goods.

Next, let us examine the impact of the CP index on riots. As discussed previously, the opportunity cost channel can explain its positive impact in urban areas and cells with monopoly groups, and the state capacity effect can be behind the estimated positive effect in more polarized areas.[31] We have also shown that, unlike in the case of organized armed-force conflict, political ethnic variables play a reduced role in the generation of riots. The lack of significance of political ethnic variables is especially evident when urban area is incorporated to the riots regression. Which suggests that the recruitment activity of organized violent groups is more successful if there is a sense of grievance in some ethnic groups, whereas this is much less important to become a temporary rioter.

Another interesting result is that the sign of the CP index is negative. Although the CP index coefficient is not always significant in the benchmark regressions, it shows again strong power and the same negative sign to explain riots in some of the robustness checks that we present next. This can be explained neither by the opportunity cost effect nor by surplus predation. Instead, it suggests an increase in state capacity to control insurgence.

6 Robustness Analysis

In this section, we perform several robustness checks. Each of them proposes a modification of the basic regression specification. All the tables containing the results are located in the appendix.

First, we study how results change if the dependent variable is conflict intensity, instead of conflict incidence. The intensity data comes from the same sources than incidence. Tables A15 to A17 show how the results in Tables A10, A12 and A13 change when the dependent variable is the number of events related to UCDP-GED organized armed-conflict, ACLED riots and ACLED violence against civilians, respectively. In general, our main findings hold in terms of sign or sign and significance. An interesting difference, though, is the negative significant signs shown by the CP index for riots (Table A16) and the interaction between consumer prices and excluded groups in the factor conflict (Table A15) and riots regressions. As explained previously, this time the only force that can be behind the sign is an increase in state capacity to control insurgence, especially in areas where the government is relatively strong, shown by its capacity to exclude certain ethnic groups from politics.

Second, Tables A18 to A20 revise the same conflict-incidence tables (A10, A12 and A13) when, instead of the GAEZ suitability and potential yield information, actual crop yields from the M3-Crop database (Monfreda et al., 2008) are employed to calculate the crop weights in the APP and CP indices.[32] Given the strong endogeneity concerns that surround the relationship between actual crop yields and conflict, numbers for year 2000 are employed to compute a time-invariant share for each crop in each cell, and the regressions are estimated for the years between 2001 and 2013 to try to diminish those problems. In this occasion we find some differences compared to our benchmark results. The main one being that the interactions of the price indices and the ethnic monopoly-group variable show sometimes the opposite signs than before.

Third, we change the source of the measure of factor conflict. It could be thought that the UCDP-GED is a very specific and non-exhaustive dataset, because it contains only certain large conflicts. To address this potential issue, Table A21 adopts the category Battles from ACLED, which assesses violent interaction between two politically organized armed groups. Recall that, unlike UCDP-GED, ACLED does not have a lower bound requirement of at least 25 battle-related deaths in at least one year. Compared to the Table A10, the main difference is that monopoly groups and the CP index show stronger importance as determinants of factor conflict. Nevertheless, the signs of all significant coefficients are the same that were estimated in Table A10, and the interpretation of the results can follow the same logic as in the previous subsection.

Fourth, we consider spillover effects from income shocks in neighboring cells. This type of effects are important on their own and have been emphasized by previous literature, like HF in the case of droughts and MB for agricultural prices, because of their potential correlation over space and time. The shocks can spill over bordering cells directly, through changes in food-prices and climate conditions, or indirectly, through changes in conflict incidence triggered by income shocks. Given that the spillovers can persist over time, we follow MB and re-estimate the regressions including as explanatory variables the contemporaneous value and two lags of the APP index and the drought index averages across the 1- and 2-degree neighboring cells.[33] Results are presented in Table A22. This table shares the same structure with Tables A23 to A28. Columns (1) to (3), (4) to (6) and (7) to (9) must be compared to Tables A10, A12 and A13, respectively; and in particular, to the results in columns (2), (10) and (12). Table A22 shows that our main findings again hold in terms of sign and significance, because spillovers do not show any power to explain conflict.

Fifth, in the main analysis, we have allowed for location-specific 5-year-lag serial correlation and cross-sectional spatial correlation in a radius of 110 km. Now, Table A23 considers spatial kernels of 55 and 1000 km and serial correlations of 2 lags and 100,000 years. Results are robust to these modifications.

Sixth, we address the modifiable areal unit problem by enlarging the cell surface. In particular, we consider cells of 110 km x 110 km and 220 km x 220 km and present the findings in Tables A24 and A25, respectively. When the areal unit is 110 km x 110 km (Table A24), results are robust in terms of sign and many times significance. Moving now to Table A25, where the areal unit is 220 km x 220 km, we see that using a larger cell as unit of the analysis substantially modifies the results. The difference possibly comes from a greater degree of coexistence of food-producing and food-consuming areas in the same cell as its surface is enlarged; which makes more difficult separate the effects of the APP and CP indices. We can see that the significance of many coefficients vanishes. For example, only five coefficients remain strongly significant in columns (3), (6) and (9); importantly, out of those, most are consistent with our main results.

Seventh, we extend the number of lags of all the variables included in the regression from two to five (Table A26). As we can see, our main results are generally robust: the estimated coefficient signs are maintained and many times their significance. Interestingly, we find again a negative and significant sign for the CP index in the riots regression as we did in our first robustness test that adds evidence in favor of state capacity as a way to control rebellion.[34]

Eighth, an alternative estimation method for binary dependent variables is employed, namely, a conditional fixed-effect logit model (Table A27). Results are most of the time robust in terms of signs, but coefficients many times are not significant. This loss of significance is not surprising, because the conditional logit only uses observations that show an incidence equal to one for the estimation, and then the number of observations is reduced from about 140,000 in the main analysis to around 20,000 with the logit.

Finally, the annual average SPEI indicator along with the variables temperature and rainfall are added to our benchmark regressions (Table A28). As we can see, our main results are robust to this modification.

In sum, the findings obtained in Section 5 are generally robust. The main exceptions are when we use actual crop yields to construct the shares and when the size of our cells increases to 220 km x 220 km. We have argued, however, that these two scenarios are less suitable for our purposes than our main specifications. Overall, 72% of the estimated coefficients obtained with the full regressions in the robustness section agree with the main analysis in terms of either non-significance or sign and significance.

7 Conclusions

This paper has studied how agricultural-commodity shocks across ethnically-diverse cells affect several definitions of conflict outcomes. 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 1998-2013 with a spatial resolution of 0.5 x 0.5 degree latitude and longitude (equivalent to 55 km x 55 km at the equator). Our main contribution has been to disentangle whether ethnic political status and diversity serve as amplifying mechanisms of the effect of income shocks on conflict.

We have obtained multiple interesting results that identify the heterogeneous impact of income shocks across conflict definitions and locations, and the importance of ethnic cleavages to understand it. In general, our results are consistent with the ones found by MB but add new aspects that suggest important differences among the determinants of factor conflict (or battles), violence against civilians and riots, and a greater role of state capacity and grievance as determinants of conflict.

First, violence against civilians clearly arises as an intermediate type of conflict that lies between battles and riots. Specifically, violence against civilians shares with battles the negative direct response to producer prices, and a significant role of ethnic political status and diversity in the transmission process; whereas it shares with riots a significant positive effect of consumer prices in urban areas and ethnically diversified cells. Furthermore, we have shown that differentiating between organized armed-force conflict (battles and violence against civilians) and non-organized violence (riots) is more informative about the determinants of conflict than between large-scale factor conflict and low-scale output conflict (violence against civilians and riots). Nevertheless, in general, differentiating the three categories seems to be preferable. We have also found that large geographical units (220 km x 220 km) do not seem to allow getting clean results; which is consistent with the inconclusive evidence found at the country level.

Second, our results emphasize an important role of opportunity costs in the decision of getting involved in any type of violence and that the existence of excluded and monopoly ethnic groups can amplify the perception of those costs. This shows up both in the negative impact on organized armed-force conflict of the opportunity cost channel in food-producing cells, and its positive impact on output conflict in food-consuming areas.

Third, we also show evidence of the importance of state capacity. This is suggested by our finding that more ethnically polarized or fractionalized societies tend to push the effect on conflict of an increase in the APP and CP indices or a decline in droughts towards a positive sign. The reason is that a larger degree of ethnic diversity signals weaker governments that are able to benefit less from the rebellion-repressing capability offered by positive income shocks. The state capacity channel seems to be stronger in the case of riots. In particular, besides its indirect effect through ethnic diversity, consumer food-prices in our sample also have a negative direct impact on riots, which is again only consistent with an important role of state capacity.

Fourth, the consumer-price impact and the category riots respond to a much lower extent to ethnic cleavages. In particular, the weight of ethnic variables in the total effect of the CP index is always below 32%. Whereas for the producer-price index and droughts, the average contribution of ethnic heterogeneity is 73%, 28% and 68% for battles, riots and violence against civilians, respectively. As a possible explanation of the low contribution of political ethnic variables in the generation of riots, we have suggested that a sense of grievance in some ethnic groups is much less important to become a temporary rioter than permanent soldiers.

Several robustness checks have shown that these findings are, in general, robust in terms of sign and significance, as long as we focus on cell sizes where the distinction between food-production and food-consumption areas remain relevant. From a policy side, the results could be interpreted as demanding an agricultural price-stabilization mechanism, because price fluctuations affect conflict. However, as we have also shown, whether this is the case and the right type of policy should depend on the nature of ethnic diversity and violence. This important issue clearly deserves further investigation. There are also several factors that can be behind the income-shock indirect-effect channeled through ethnic cleavages, and some of them have been pointed out in the text: trust, monitoring costs, labor market frictions, and quality of institutions. Incorporating these aspects into the analysis can represent as well a promising source of future research.

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Notes

[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, as Berman and Couttenier (2015) argue, results have been mixed. At the micro-level, on the other hand, the analysis points out a more robust causal relationship. For instance, Dube and Vargas (2013), Fjelde (2015), and Berman et al. (2017) find that agricultural price shocks are negatively correlated with conflict, whereas mineral and oil prices are positively correlated.

[2]In particular, the role of ethnic fractionalization and ethnic polarization in civil wars have been studied, among others, by Montalvo and Reynal-Querol (2005), Esteban and Ray (2008 and 2011) and Esteban et al. (2012); and the importance of the presence of ethnic groups excluded from political power and ethnic groups that enjoy monopoly over the state have been analyzed, for example, by Cederman et al. (2009) and as Cederman et al. (2011).

[3]Bazzi and Blattman (2014) argue that several African nations produce a large volume of commodity output, leading to a potential endogeneity problem related to prices. For example, from the supply side, a conflict could lead to reduced production, and hence, increase commodity prices. Even though this can be important at the country level, it is much less so at the cell level.

[4]Albeit not focusing directly on violence, Brückner and Gradstein, (2015) find that, across countries, the marginal effect of oil price changes on political risk increases with ethnic polarization.

[5]See Section 5.5 for a more detailed discussion.

[6]von Uexkull et al. (2016) point out that politically excluded groups are more likely to be barred from government-sponsored compensation programs or even aid in the case of negative income shocks such as floods and severe droughts.

[7]As we can see in Figure A3 in the Appendix, most African countries have excluded ethnic groups, whereas only Angola, Mali, Rwanda, Libya, and Egypt have settled monopolist ethnic ones.

[8]See Figure A1 in the appendix.

[9]According to UCDP-GED, two-side armed force battles are classified as state-based conflict or non-state conflict, and armed-force violence against civilians as one-sided violence.

[10]http://www.imf.org/external/np/res/commod/index.aspx, https://datacatalog.worldbank.org/dataset/global-economic-monitor, and "http://gaez.fao.org/Main.html.

[11]In the robustness section, we also try alternative data on crop production from the M3-Crops dataset (Monfreda et al., 2008).

[12]http://www.fao.org/faostat/en/data/FBSH.

[13]Notice as well that, in the case of the consumption shares, endogeneity issues should be much less important due to the relative stability of consumer tastes and the possibility of importing products.

[14]SPEI stands for Standardized 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 HF, PET depends on several factors, including most notably temperature but also rainfall, sunshine exposure, latitude and wind speed.

[15]Variable definition from PRIO-GRID codebook: https://grid.prio.org//codebook.

[16]Because the sum of the shares of the territory that are occupied by each ethnic group can sum to more than one, they are re-scaled so that the sum equals one.

[17]These databases also provide information about ethnic groups that are part of power-sharing arrangements and groups that are politically dominant. We have chosen the two extremes, like Basedau and Pierskalla (2014) for example, because they seem more appropriate to capture the impact of grievance and government power.

[18]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 aggressors due the persistence of conflict. This problem is particularly important at the country level. Which has led some papers to explore

the robustness of their results to using conflict onset and conflict offset as dependent variables, because they do not suffer from this potential problem. At a cell level, however, conflicts are less persistent. As Berman and Couttenier (2015) for example argue, using cell-level observations, about 75% of conflict events do not last more than 2 years. We therefore decide not to use onset and ending as dependent variables.

[19]Conflict intensity is not a binary variable. It gives the number of events in a given year and cell.

[20]Other standard controls employed by the literature include geographic characteristics, population size and satellite night lights (see, e.g., Alesina et al., 2016). We do not use them as regressors because the geographic characteristics are time invariant, and therefore, their effect is subsumed in the cell dummy, and population and night lights suffer from strong endogeneity concerns with conflict and the latter can also possibly generate a post-treatment bias.

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

[22]Reporting the sum is desirable at least for two reasons. To start with, the sum gives a more direct idea of the total effect of the shock. In addition, if the regressor is highly correlated over time or space, the sum is estimated with much more precision (see, e.g., MB). In the appendix, Figures A7 to A12 present the results for the different lags of interaction variables that are significant in the full regressions—columns (10) and (12).

[23]Previous literature, however, has found different results. For example, at the country level, Janus and Riera-Crichton (2015) and Gimenez-Gomez and Zergawu (2018) 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 find that both variables have a well-defined effect for all definitions of violence.

[24]The model associated to column (11) gives very similar results.

[25]In HF, the estimated coefficient is negative because they use a reversed scale. That is, in our regressions, SPEI growing season is introduced such that higher values of the variable imply a higher incidence of droughts; whereas in their work, they imply lower drought incidence.

[26]A sufficient condition for the significance of the difference between the marginal effect when the ethnic variable takes on zero and when it takes on positive values is that the corresponding confidence intervals do not overlap over the range shown in the vertical axis. However, this is not a necessary condition, because the two marginal effects are perfectly positively correlated.

[27]The impact is computed as a marginal effect as follows. For a single independent variable, it is given by its standard deviation times the estimated coefficient multiplied by 100. For interaction terms X*Y,

where X is the variable of interest, the marginal effect follows the same procedure described previously but multiplying also by the variable Y's mean. Finally, the implied total impact is the sum of the marginal effects across all the terms that contain the variable of interest.

[28]MB does not find significant the CP index, neither in the factor conflict regression, nor in the output conflict specification when year fixed effects are included, which in our case are always controlled for. They argue that consumer prices vary more over time than across space, and therefore, the inclusion of year fixed effects absorb a big part of the impact.

[29]This is consistent with the work of Hendrix and Haggard (2015) for example.

[30]The same effect is found by von Uexkull et al. (2016) for droughts in areas with excluded groups.

[31]There is, though, a possible alternative interpretation for the last result. The moderation of the state-capacity effect by polarization/fractionalization might be stronger in food-producing cells, and therefore, the positive sign in food-consuming areas can be still mainly capturing an opportunity cost mechanism. Notice that this alternative argument, although possible for the CP index, cannot be applied to food-producing cells, because there the negative sign is only compatible with the state-capacity channel.

[32]The M3-Crop database is available at https://mygeohub.org/groups/drinet/cropdata.

[33]Estimation of the effects derived from the CP index cannot be implemented because it is a country-level aggregate. Notice also that we do not include the realizations of the outcome variable in bordering cells in this spillover regressions. As argued by Berman et al. (2017) and MB, among others, the reason is that the identification of spillovers is problematic, and introducing spatial lags of the dependent variable can generate a clear simultaneity bias due to its temporal persistence.

[34]When urban area and its interaction with the CP index are introduced in the riots regression, the CP index maintains its negative sign and CP*Urban shows a positive sign, and both are significant. This occurs with the intensity and 5-lags specifications.