**Agricultural Windfalls and the Seasonality of Political Violence in Africa[[1]](#footnote-1)**

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**Abstract**

We study the seasonality of violence against civilians in the cropland of Africa. We combine monthly international cereal prices with grid-cell level cropland area fraction and harvest seasons to investigate the relationship between agricultural income shocks and violent attacks by different military groups. We find that violence in the cropland is associated with price increase, and the effect is apparent during the early post-harvest season, when the value of spoils to be appropriated is highest. Among considered perpetrators, we find political militias as the most likely force behind the seasonal violence in Africa.

**Keywords**: Africa; Cereals; Conflict; Prices; Seasonality.

**JEL Codes**: D74; O13; Q02.

**Introduction**

In low–income economies with weak institutions, a change in people’s income may exacerbate unlawful or violent activities. In regions where agriculture is an integral part of the economy, growing empirical evidence suggests connections between crop yields and conflict (Wischnath & Buhaug, 2014; Buhaug et al., 2015; Koren and Bagozzi, 2017; Koren, 2018; Vestby, 2019) as well as commodity price shocks and conflict (Dube and Vargas, 2013; Maystadt & Ecker, 2014; Raleigh, Choi, & Kniveton, 2015; Berman and Couttenier, 2015; Fjelde, 2015; Crost and Felter, 2020; McGuirk and Burke, 2020); all pointing to the plausibly causal relationship between agricultural income shocks and conflict.

In examining this linkage, previous studies have relied on yearly conflict and price data observed either at the country level (e.g., Miguel et al., 2004; Brückner and Ciccone, 2010; Bazzi and Blattman, 2014), or at the grid cell level (e.g., Fjelde, 2015; Berman and Couttenier, 2015; Berman et al., 2017; Harari and Ferrara, 2018). Such yearly estimations may conceal important seasonal patterns, however. The few studies that applied temporally more disaggregated data, did not specifically examine the role of seasonality in the income–conflict nexus (e.g., Maystadt and Ecker, 2014; Smith, 2014; Bellemare, 2015). While offering evidence of a linkage between agricultural income and conflict, these studies, by design, do not investigate the important seasonal variations in this relationship, and thus do not capture the role of the harvest itself in conflict. Alternatively, the studies that offer insights of the seasonal nature of agrarian conflict, rely on annual units of observations and, thus, do not explicitly model the pattern of seasonality (e.g., Harari and Ferrara, 2018; McGuirk and Nunn, 2020).

We contribute to the knowledge of the income–conflict nexus by linking political violence with the seasonality of agricultural income. The only other work that directly examines the harvest-related seasonality in conflict incidence is that of Guardado and Pennings (2020) who study the effect of the harvest season on conflict intensity in Afghanistan, Pakistan, and Iraq. Another recent study that indirectly assesses the harvest-time conflict is that of McGuirk and Nunn (2020) who investigate the impact of climatic shocks on conflict between pastoralists and agriculturalists in Africa. Our research differs from the above two studies in that we link conflict incidence with plausibly exogenous harvest-time income shocks that originate from the variation in the international cereal commodity prices. To that end, our research differs from a growing body literature on the effect of price shocks on conflict (e.g., Dube and Vargas, 2013; Bazzi and Blattman, 2014; Berman and Couttenier, 2015; McGuirk and Burke, 2020) in that we analyse monthly data, thus explicitly estimating seasonal patterns in the relationship between agricultural windfalls linked with crop harvest season and violence against civilians.

We analyse 24 years of monthly data from January 1997 to December 2020, covering 2538 one-degree grid cells across 51 African economies where agriculture is the key source of income, and where civil unrest and violence are, by and large, part of daily life. We find evidence of a seasonal pattern of violence—specifically attacks against civilians—and plausibly link it with changes in harvest–related windfalls in the cropland of Africa. The apparent link between agricultural income and violence primarily stems from an increase in attacks by militias connected to political elites during intra-regime contestation. We suggest this violence may intensify during harvest times because this is when the perpetrators can maximize their opportunities for appropriation of agricultural products, as well as do the most damage to their opponents and opponents’ supporters, thus shifting the political landscape in favour of their elite patrons. We test this rapacity mechanism by examining patterns of seasonality in good and bad harvest years. In so doing, we confirm that post-harvest conflict seasons tend to widen in years with ample rainfall during the crop growing season, and tend to shrink in years with large number of excessively hot days during the crop growing season.

This finding is economically meaningful, as it suggests a likely income–related temporal displacement of conflict in the croplands of Africa. It is also politically important, inasmuch as the nature of the conflict actors that are driving the seasonality of conflict suggests that the goals of the groups, and their means of raising revenue, are important to understanding the temporal dynamics of conflict associated with agricultural production.

**Background and Context**

In this study, we define ‘conflict’ as a deviation from what would be considered *normalcy*in the ways that people or groups of people interact and bargain with each other. This leads to a wide spectrum of incidents that could qualify as data points, ranging from peaceful protests to altercations among neighbours to extreme forms of mass violence. These events differ from one another in their scope and impact; the motivations of those involved vary as well. Here, we focus on conflict incidents that are directly or indirectly linked with the food and agricultural sector – attacks on civilians within conflict-affected countries’ crop-producing regions.

Many of the theories that explain the linkage between income and conflict are based on the notion of a trade–off between *farming*and *fighting*, whereby income from the former is an opportunity cost of the latter. The opportunity cost of fighting is seen as an increasing function of income—a negative income shock leading to more violence (Collier and Hoeffler, 1998; Bazzi and Blattman, 2014). Alternatively, a drop in farm income reduces the value of spoils to be appropriated, which can mitigate violence (Berman and Couttenier, 2015). The net effect of income shocks on conflict is thus ambiguous as illustrated by a large body of literature on the topic (Blair et al., 2021).

McGuirk and Burke (2020) argue that data aggregation (to the country level) may be an important reason for the ambiguous (or null) results. They show, using geographically disaggregated grid cell–level data, a positive and statistically significant relationship between cereal crop prices and conflict. More specifically, McGuirk and Burke (2020) define two broad categories of conflict, *factor conflict* and *output conflict*, based on actors’ motivations. Factor conflict involves actors engaging in battles for control of a territory to seize its discounted expected returns. This type of conflict tends to be long lasting. The aim of output conflict is to appropriate surplus. This type of conflict, compared to the factor conflict, is more transitory.

Conflicts that can be linked with farm income fall into the output conflict category for several reasons. First, agriculture is a labor–intensive sector, with large–volume and low–value output. Thus, ‘rent–seeking’ may not necessarily apply in this sector (in contrast to the diamond mining sector, for example). Second, agricultural output is a readily available source of food and feed, and thus is an attractive target for perpetrators that are attempting to extract resources without controlling territory (e.g., Koren and Bagozzi, 2017). If conflict associated with agricultural production is better characterized as output conflict than factor conflict, the expectation for the seasonality of conflict would be that conflict incidents would increase during the harvest period when there is surplus to be appropriated. In addition, the types of the actors involved in that increase in conflict would vary based on their goals and motivations – actors that are engaged in output conflict would be more likely to increase their attacks during the harvest period than groups engaged in factor conflict.

*The seasonality of conflict*

A distinctive feature of agricultural production—and, therefore, of agricultural income—is its seasonality. Conflict, due to intermittent employment in the agricultural sector throughout the crop year as well as the abrupt influx of income shortly after harvests, is likely to also have a seasonal pattern. Ample anecdotal evidence points to harvest–related violence and altercations. We present several instances here. These are from the Armed Conflict Location & Event Data (ACLED) Project (Raleigh et al., 2010), which we describe in more detail below. The incidents take the form of rapacity or retaliation, and typically involve attacks at the time of crop harvesting or transportation. For example, a record indicates that in March 2017, gunmen shot and killed a farmer as he resisted an attempt to loot his sorghum on his way to market in Kwajieno County in Wau (South Sudan).

These incidents usually are linked to certain violent groups. For example, in August 2015, Boko Haram raided the village of Awonori (Nigeria), killed seven residents, and carted away food supplies and livestock. In July 2016, Perci beat a farmer in Mbulula (Democratic Republic of Congo), and stole a bag of rice. In July 2019, Ahlu Sunna Waljama’a (ASWJ) attacked farmers harvesting rice in Malinde (Mozambique), burned plantations, and stole food.

Many of the incidents are manifestations of ongoing conflicts between pastoralists and agriculturalists. For example, in September 2017, armed pastoralists killed a farmer and looted his food in Bau locality in Blue Nile (Sudan). In June 2018, Fulani herdsmen attacked Tsedyugh (Nigeria) and killed 19 farmers, destroying their property, foodstuffs, and personal belongings.

The specific mechanism that connects the harvest and conflict could mean either an increase or a decrease in conflict during harvest time. The intermittent nature of agricultural employment lends itself well to the *opportunity cost mechanism* of conflict in the agricultural sector. Guardado and Pennings (2020) investigate this mechanism of conflict seasonality, and show that in Afghanistan, Iraq, and Pakistan, the onset of the harvest of cereal crops tends to *reduce* conflict. However, as Balcells and Stanton (2021) point out, the ‘logic of violence’ and the ‘logic of recruitment’ are not equivalent. Decreasing opportunity costs to joining a rebellion (from, for example, lower wages in the ‘legitimate’ sector) do not *per se* mean that individuals will join a rebellion and engage in violence. In addition, precisely because individuals may have an incentive to join a violent group in one location, but may commit violence in a different location, violence, particularly *strategic* violence, may not be directly tied to incentives to join a violent group in a specific location.

Alternatively, a harvest–time positive income shock increases farmers’ wealth relative to that of the rest of the population, which creates incentives for the latter to target the former through robberies and abductions. This lends itself to the *rapacity mechanism* of conflict (e.g., Dube and Vargas, 2013), which in the agricultural sector can quite possibly be seasonal. The incentives for looting and appropriation of agricultural surplus are likely to be the strongest shortly after the harvest and dissipate gradually as the crop year progresses. Moreover, the higher the value of a crop, the more likely it is that a farmer will engage in a conflict with potential perpetrators. In this mechanism, conflict intensity should *increase* during and immediately after the harvest season.

*The role of conflict actor type in conflict*

At the heart of the question of the link between agricultural production and conflict, including the seasonality of conflict, is not only the *mechanism* by which income shocks lead to conflict intensity, but also *who* is engaging in violence. In the ACLED data project, conflict actors are divided into four categories, depending on who is supporting them, and the nature of their goals (Raleigh et al 2010). *State forces* are those performing government functions, including military and police functions, in a given territory. This attribution does not imply legitimacy, however. Rather, it acknowledges the *de facto*exercise of state control over a territory. *Rebel groups* are those with a political agenda to secede from or overthrow a ruling regime, typically by means of violent acts – they are generally from large groups that are excluded from state institutions. *Political militias* are a diverse group, which do not defend or seek the removal of the *de facto*regime. Rather, they are typically associated with and supported by a political elite, such as a recognized government, rebel organization, political party, business elite, or opposition group. *Identity militias* represent armed groups organized around some common feature such as a community, ethnicity, region, or religion.

While there is significant overlap, these different conflict actors vary in the location, targets, modality, and fatality rates of their violence (Raleigh, 2012; Raleigh & Choi, 2017; Choi & Raleigh, 2021). Rebel groups engaged in civil wars are likely to attack mostly state forces (although they also attack civilians) over a relatively long period of time, in areas that are dominated by politically marginalized, large groups. Identity militia violence may occur in politically marginalized areas, operating on behalf of politically marginalized groups that do *not* have the resources to create organized rebel groups. Violence may be directed against other identity militias, or against civilians in opposing ethnic or regional groups (Raleigh, 2014).

In general, political militias represent a category difference in violence, compared with other types of conflict actors. First, temporally, political militias’ violence often takes place outside of civil wars episodes. Second, political militia violence increases as a regime transitions from authoritarianism to democracy (at least in Africa) – it is not *per se* a result of authoritarian, oppressive practices (Raleigh & Kishi, 2020). Political militias are tools of elites within a country that serve as a means of competing for power, or more specifically, for maximizing their own power and access to positions and resources within the state. As such, political militias can be seen as intra-elite conflict actors, rather than engaging in inter-elite violence. Their violence is spatially localized in areas dominated by groups that are included within the dominant power structures of the state, and political militia-related attacks are often lower in the number of casualties compared to civil war violence (Raleigh, 2014).

Political militias are used when the state, or elites within the state, face either *internal* threats or *domestic* threats. In internal threats, politicians are engaged in contestation with other politicians, and in conflicts, political militias are used to fight other political militias. In domestic threats, rioters or opposition militias are opposed by pro-government militias. In this formulation, political militias represent an alternative to the use of state forces, which are primarily for use against rebel groups, not against less organized militias, localized political elites, or (unorganized) civilians. State forces are expensive to use relative to political militias and, in a fragmented regime, their loyalty may be questionable (Raleigh & Kishi, 2020).

The involvement of political militias in a conflict can lead to a general increase in mass killing of civilians (Koren, 2017), perhaps because governments (particularly semi-democratic regimes) outsource their killing to pro-government militias as a way of providing plausible deniability and avoiding accountability (Carey, Colaresi, & Mitchell, 2015). This does not necessarily mean that pro-government militias are a substitute for state violence – political militias may simply collaborate with states in engaging in violence (Stanton, 2015). In addition, pro-government militias do not necessarily increase attacks on civilians by the state, inasmuch as they may be able to provide information about the local population that can decrease the need for the state to use violence, particularly if the militias are the same ethnicity as the insurgent-supporting population (Lyall, 2010).

*Linking the actor types with the seasonality of conflict*

The variation in patterns of violence for different groups is likely to carry over to the relationship between violence, and agricultural production and seasonality as well. Seasonality (or lack thereof) of conflict can be explained by a combination of (1) *why* different conflict actors might target civilians, and (2) *how* the groups raise revenue. The seasonality of some actors’ violence, but not others, can be explained by a combination of three factors: the extent to which the actors are attempting to control territory, the location of their violence, and the time frame of the violence in which the actors are engaged.

There is territorial and temporal variation by different types of conflict actors, even within the same state. Rebel groups will likely operate in areas that have been excluded from, or subject to discrimination by state institutions. Rebel group violence, in response to this discrimination, is likely to be long-term. Identity militias that engage in communal violence are likely to operate in geographically peripheral (potentially ‘ungoverned’) areas of the state in short, sharp, geographically contained violent campaigns. Political militias, on the other hand, operate in areas that are included in state institutional power structures. Crop-producing areas are likely to be within these structures. Inasmuch as political militias are engaging with other elites, they engage in "short periods of high violence and targeted fatalities" in wealthy, accessible regions of the state (Raleigh, 2014). The temporal and territorial differences among the conflict actors can explain why political militias, but not rebel groups or identity militias (or state forces) would experience seasonality of conflict centred around the harvest season.

Political militias have three characteristics that can lead to seasonal attacks on civilians in crop-producing regions (Appendix Table 1). First, because they are generally linked to the state (or elements within the state), they do not seek control territory on their own, and thus do not establish long-term control of, or long-term extraction of resources from territory. Second, relatedly, because they are engaged in violence on behalf of elite patrons, they generally operate in areas already controlled by the state, and included within state institutions, which are generally crop-producing regions. Third, their violence is generally short-term and targeted at enemies of their elite patrons, meaning that, when extracting resources from where they are operating, they are more likely to extract short-term resources. When attacking their enemies, they are likely to increase their attacks when their enemies are realizing their income, which in crop-producing regions is likely to be during harvest time.

Conversely, other types of conflict actors have characteristics that can mitigate against seasonal attacks in crop-producing regions. Because state forces and rebel groups are engaged in long-term violent campaigns, and aim to control territory (and extract resources from that territory over the long term), they are less likely to vary their violence on a seasonal basis, and to the extent they are engaged in violence over expropriation of resources, are engaged in factor conflict, where there are not seasonal variations in their ability to expropriate resources. Because rebel groups and identity militias are often operating in territory that is excluded from state institutions, or peripheral and ‘ungoverned’ in general, they are also less likely to be operating in crop-producing regions, suggesting that their ability to expropriate seasonally varying agricultural surplus, or to maximize harm to their opponents in crop-producing regions on seasonal basis, is limited.

**Table 1: Percentage attacks by different conflict actors by regional crop production status**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Non-cropland** | **Cropland** | | | |
| **Actor types** | *Cropland area fraction* | | | | |
|  | *0.000* | *>0.007* | *0.007–0.029* | *0.029–0.055* | *<0.055* |
| *State forces* | 3.1% | 21.2% | 35.9% | 26.7% | 13.1% |
| *Rebel groups* | 4.7% | 28.3% | 36.0% | 24.4% | 6.5% |
| *Political militias* | 3.3% | 21.3% | 39.3% | 25.6% | 10.5% |
| *Identity militias* | 9.4% | 23.7% | 29.2% | 15.2% | 22.4% |

Note: The values are based on the data used in this analysis, which covers 2538 one-degree grid cells across 51 African economies over the 24-year period between January 1997 and December 2020. 0.007 is approximately the 50th percentile area fraction, 0.029 is approximately the 80th percentile area fraction, and 0.055 is approximately the 90th percentile area fraction.

This spatial variation in attacks among different groups can be seen in the proportion of attacks staged by different types of conflict actors inside crop-producing regions and outside crop-producing regions (Table 1). The proportion of attacks in crop-producing regions is highest for state forces and political militias, and the proportion is essentially the same for both group types, suggesting that they are largely attacking in the same areas (or at least attacking in crop-producing regions). By contrast, rebel groups and identity militias stage attacks more frequently in non-crop-producing regions, which in an agrarian state would accord with regions that are marginalized from state institutions, whether through exclusion or discrimination, or through their peripheral, ‘ungoverned’ status.

**Data**

We obtain publicly available data on conflict, crop harvest, and cereal prices, from multiple online sources. The conflict and price data are recorded at monthly intervals and span the January 1997 – December 2020 period; the conflict and crop harvest data include 51 countries and territories, covering 2538 one-degree grid cells across Africa. Of these, 1435 cells had at least one conflict incident during the study period; 1764 cells have some cropland area, and in 773 instances, this area covers at least one percent of the cell.

*Conflict*

We draw data on conflict from the ACLED Project[[2]](#footnote-2) (Raleigh et al., 2010), available at [https://acleddata.com/.](https://acleddata.com/) The current version of the dataset groups events into six categories. Of these, we use events categorized as ‘violence against civilians.’ That is, we discard ‘battles,’ ‘strategic developments,’ and ‘explosions/remote violence,’ as these typically involve longer term and larger scale conflict between *de facto* government and rebel groups, and are less likely to be triggered by seasonal food shortages or monthly price shocks. We also discard ‘protests’ and ‘riots’ as these are more prevalent in non-agricultural/urban areas and may be motivated by different factors and characterized by different dynamics from that of the form of conflict considered in this analysis. Finally, we discard events with geo-precision code 3, which assigns an incident for which the exact location is unknown to a provincial capital, to avoid adding measurement error to the data. We maintain all time-precision levels, as the least accurate level in the database still gives the correct month. As a result, we analyse a total of 55,942 unique incidents that occurred between January 1997 and December 2020 across 51 countries/territories in Africa. Appendix Figure 1 presents the country ranking by prevalence of violence over the study period, as well as the geographical distribution of observed incidents.

The ACLED Project aggregates actors into four distinct categories (Raleigh et al., 2010): *state forces*, *rebel groups*, *political militias*, and *identity militias*. Violence by different actor types varies geographically both within Africa as a whole, and within countries (Figure 1). While the reported incidents cover most of the populous parts of the continent (See Appendix Figure 2 for the population map of the continent), some geographical disparities are apparent. In general, violence against civilians is more prevalent in subequatorial countries, with a disproportionately large incidence in perennial conflict locations. There is also geographic disparity in prevalence of conflict incidents by actor types. The involvement of state forces in conflict manifests across all of Africa, particularly in its most populous areas. The same is true for political militias, which have proliferated across Africa as countries have democratized and competition for power within the state has increased (Raleigh, 2016). Rebel groups and identity militias are endemic to the equatorial part of Africa, but there appears a somewhat limited geographic overlap between the two, certainly compared to more evidence overlap between state forces and political militias. Among these four actors, majority of the violence has been attributed to political militias.

Map

Description automatically generated

**Figure 1: The geographic distribution of conflict by actor type**

*Note:* The graphs are based on the data used in this analysis, which covers 2538 one-degree grid cells across 51 African economies over the 24-year period between January 1997 and December 2020. Only grid cells with at least one incident over 1997-2020 period are featured. The values are the total number of incidents in a grid cell during the study period.

*Crop harvest*

We obtain the data on crop production and crop growing seasons from Sacks et al. (2010), available at [https://nelson.wisc.edu/sage/data-and-models/crop-calendar-dataset/index.php.](https://nelson.wisc.edu/sage/data-and-models/crop-calendar-dataset/index.php) We consider four cereal crops: maize, sorghum, wheat, and rice. For each of these crops, we obtain the fraction of the cropland within a grid cell. In multi-crop cells, we consider the major crop as that with the largest fraction of the cropland. Finally, we obtain the harvest month for the major crop in each grid cell. These remain fixed over the study period. The geographic distribution and production intensity of the considered major crops are illustrated in the left panel of Figure 2.

Map

Description automatically generated

**Figure 2: The geographic prevalence of cereal crops and their prices over time**

*Note:* Only grid cells with non-zero cropland are featured. Prices are mean–centred and log–transformed.

*Cereal Prices*

We source commodity price data from the International Monetary Fund (IMF), available at [https://www.imf.org/en/Research/commodity-prices.](https://www.imf.org/en/Research/commodity-prices) These prices are denominated in US dollars per metric tonne. For purposes of presentation, as well as econometric analysis, we mean-center and log-transform these price series. These price series are presented in the right panel of Figure 2. As seen, while they tend to co-move, there are episodes of divergence among some cereal prices.

*Auxiliary Data*

We use data on the world population from the Center for International Earth Science Information Network at Columbia University (CIESIN, 2018), available at [https://sedac.ciesin.columbia.edu.](https://sedac.ciesin.columbia.edu/) Population estimates are available for 2000, 2005, 2010, 2015, and 2020. Using these estimates, for each cell, we interpolate the population data for all other years in the 1997–2020 range, using a cubic spline method. We include these time-varying population estimates as a control variable in the regressions.

We obtain ERA5 reanalysis data on gridded daily 2m above the surface air temperatures and monthly averaged total precipitation from European Centre for Medium-Range Weather Forecasts (ECMWF) Copernicus Project, available at https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels. For each grid cell and year, we obtain the relevant measures of these weather variables as follows. For the temperature data, we obtain daily 2:00 pm temperatures, which we convert from Kelvin to Celsius and average to the 1-degree grids. We then obtain the count of days, during the months between the planting and harvesting seasons (Sacks et al., 2010), when the observed temperature exceeds 32 degrees Celsius—an approximate threshold beyond which higher temperatures can be damaging for plant growth, and thus crop yield. We use this count variable as a measure of weather adversity during the growing season for the current harvest. For the precipitation data, we obtain monthly total precipitation, which we aggregate to the 1-degree grids. We then calculate the measure of total precipitation during the months between the planting and harvesting seasons as above. We use these weather variables to test the rapacity mechanism proposed in this study.

We obtain the Uppsala Conflict Data Program (UCDP) Georeferenced Event Dataset (global version 21.1), available at https://ucdp.uu.se. These data have been used extensively in the empirical literature, often alongside with the ACLED data (e.g., McGuirk and Burke, 2020; McGuirk and Nunn, 2020), and can present some complementary information to the ACLED data (e.g., Eck, 2012). For the purposes of this study, we retained those observations from the 1997—2020 period that were recorded as ‘one sided violence’ events and were identified with the certain precision at temporal (exact date or month or within up to a 30-day range of the event) and spatial (exact location or within a maximum of 25 km radius of the location) levels.

**Empirical Strategy**

In what follows, we denote a cell with subscript *i*, a year with subscript *t*, and a month after harvest with subscript *h*. The main econometric specification is as follows:

(1)

where is a binary variable that denotes the incidence of violence *h* month after harvest in cell *i*, in year *t*; is the *agricultural income shock*, where is the seasonally differenced log-transformed price of a major crop in cell *i*, and is the time-invariant cropland area fraction in cell *i*; , *h=0,…,11*, are the cell-specific seasonal dummy variables that take value of one when the period of observation is *h* months after harvest. These seasonal dummy variables correspond to a crop year, rather than a calendar year, and vary across cells due to differences in climatic conditions and the specificity of growing conditions for the major crop in each cell (see Appendix Figures 3 and 4 for growing seasons and harvest periods of major crops across countries). is a cell fixed effect and is a country–year fixed effect. is the error term.

The identifying assumption in equation (1) rests on the premise that changes in conflict incidence in cells with no cropland provide a good counterfactual for changes in conflict incidence that would have been observed in cells with cropland had there been no harvest-related windfall. For this assumption to hold, the agricultural income shocks should be exogenous to violence observed across locations, conditional on cell fixed effects that capture any time-invariant determinants of conflict (e.g., distance to roads, cities, or state borders), and country-year fixed effects that capture within-country common shocks (e.g., inflation, exchange rates, change in governance, etc.), as well as possible changes in the quality of the data collection/reporting over time. The components of the agricultural shock ensure of this. We use international prices, which are unlikely to be affected by conflict in Africa (see also Bazzi and Blattman, 2014; McGuirk and Burke, 2020), rather than local prices to avoid the issue of reverse causality when conflict may have disrupted local markets (e.g., Hastings, et al 2022). We maintain the cropland area fraction and harvest month fixed for each cell to avoid the issue of reverse causality associated with instances when conflict may have caused changes in crop production or harvest timing.

The estimated coefficient,  , reflects the effect of a change in price growthon the incidence of violence in *h* months after harvest in a hypothetical location with 100 percent cropland. A positive value of the coefficient implies that an increase in the crop price relative to its level from a year ago,[[3]](#footnote-3) which under the efficient market hypotheses entails a positive price shock relative to the expectation, is associated with an increase in the probability of violence in that month of the harvesting year in the agricultural cell relative to the non-agricultural cell, and that this effect is more pronounced in cells with the higher fraction of cropland. Notably, the cropland area fraction in each given cell is typically low, with an average value of 0.02, or two percent of the area of the grid cell (see Appendix Figure 5). We thus scale the estimated coefficient accordingly, when presenting the magnitude of the expected impact of the price shock in the cropland.

**Results**

Table 2 summarizes the main set of results of this study. The first column of the table includes parameter estimates associated with violence by any actor. The subsequent four columns include parameter estimates associated with violence by each actor, to account for heterogeneity in the ways different actors may contribute to conflict. In all instances, the standard errors are adjusted to clustering at the levels of cell and country-year (as part of the robustness checks, we show the inference is invariant to different levels of clustering).

When we examine the effect of agricultural windfalls on violence against civilians using combined data, while the seasonal pattern manifests itself. When we separately assess the effect of agricultural income shocks across different types of conflict actors, the evidence points to *militias*, and most prominently to *political militias*,as the dominant actors contributing to violence in the agricultural regions of Africa, particularly as it relates to the seasonality of conflict. *Rebel groups* do not act any different in response to the considered commodity price shocks or around the harvest. *State forces*, if anything, appear to be less violent after harvest related income shocks, though the effect is small and not statistically significant.

**Table 2: Crop year seasonality of violence due to income shocks**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Violence by | Violence disaggregated by: | | | |
|  | All actors | State  forces | Rebel  groups | Political militias | Identity militias |
| *Variables* |  |  |  |  |  |
| shock×d0 | 0.132 | -0.097 | -0.016 | 0.224\*\* | 0.072\*\* |
|  | (0.113) | (0.063) | (0.058) | (0.097) | (0.030) |
| shock×d1 | 0.222\*\* | -0.040 | 0.021 | 0.203\*\*\* | 0.023 |
|  | (0.095) | (0.055) | (0.045) | (0.064) | (0.030) |
| shock×d2 | 0.090 | -0.079 | 0.030 | 0.107 | 0.046 |
|  | (0.098) | (0.057) | (0.040) | (0.086) | (0.033) |
| shock×d3 | -0.210\* | -0.101 | 0.007 | -0.061 | -0.001 |
|  | (0.110) | (0.071) | (0.047) | (0.071) | (0.028) |
| shock×d4 | -0.017 | 0.014 | -0.049 | -0.030 | 0.045 |
|  | (0.120) | (0.072) | (0.037) | (0.060) | (0.044) |
| shock×d5 | -0.125 | -0.113\* | -0.020 | -0.095 | 0.031 |
|  | (0.096) | (0.063) | (0.049) | (0.069) | (0.033) |
| shock×d6 | -0.062 | -0.032 | -0.027 | -0.018 | 0.008 |
|  | (0.105) | (0.049) | (0.036) | (0.070) | (0.068) |
| shock×d7 | 0.055 | 0.040 | 0.014 | -0.007 | 0.060 |
|  | (0.079) | (0.052) | (0.036) | (0.049) | (0.044) |
| shock×d8 | 0.018 | -0.059 | 0.042 | 0.057 | -0.004 |
|  | (0.077) | (0.045) | (0.033) | (0.061) | (0.030) |
| shock×d9 | -0.007 | 0.008 | -0.031 | -0.027 | -0.017 |
|  | (0.080) | (0.050) | (0.041) | (0.054) | (0.032) |
| shock×d10 | 0.157 | 0.002 | 0.018 | 0.133 | 0.068 |
|  | (0.096) | (0.034) | (0.037) | (0.088) | (0.043) |
| shock×d11 | 0.055 | -0.006 | 0.018 | 0.011 | 0.062 |
|  | (0.094) | (0.057) | (0.038) | (0.076) | (0.045) |
| *Controls* |  |  |  |  |  |
| Cell FE | Y | Y | Y | Y | Y |
| Country-year FE | Y | Y | Y | Y | Y |
| ln(population) | Y | Y | Y | Y | Y |
| *Descriptive statistics* |  |  |  |  |  |
|  | 0.034 | 0.009 | 0.008 | 0.018 | 0.006 |
|  | 0.046 | 0.012 | 0.010 | 0.025 | 0.007 |
|  | 0.021 | 0.021 | 0.021 | 0.021 | 0.021 |
| Number of conflict incidents | 55,942 | 10,613 | 11,674 | 26,195 | 6,725 |

*Note:* the dependent variable is a binary variable that depicts the incidence of political violence; shock is the annual growth of the price for the major crop in a cell interacted with the cropland area fraction in the cell; dh is the crop year binary seasonal variable where *h* depicts the month from harvest; all regressions include cell and country-year fixed effects, and a control of log(population); the values in parentheses are standard errors adjusted to clustering at the level of a grid-cell and a country-year; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels.

Focusing on political militias, the results offer compelling evidence of a significant increase in violence shortly after harvest. To put the parameter estimates in context, we calculated the seasonal effects of a one standard deviation price shock (approximately 25 percent annual growth) on probability of violence by four considered actors, evaluated at the average of the observed cropland area fraction, relative to the baseline probability of violence in the cropland (approximately 2.5 percent). For example, based on this calculation, the estimated coefficient 0.222—associated with the first month after the harvest period—translates to a 2.6 percent increase in the probability of violence.

Figure 3 illustrates these seasonal effects. The top of the radial plots corresponds to the harvest month, with the subsequent months appearing clockwise. Solid curves are the estimated percent changes in the probability of conflict, while the shaded regions represent 95% confidence intervals. The dashed lines depict zero, while dotted lines mark four precent increments on each side of the zero line. The effect is statistically significant at 5% level where the shaded region does not overlap the zero line at any given month of the crop year.

As noted above, there is no evidence of considerable changes in violence by state forces or, especially, rebel groups. There is evidence of seasonal violence by political militias and, to a lesser extent, by identity militias. There is difference in the seasonal pattern of violence by these two actors, however. With political militias, we observe an increase in violence at harvest time, which extends for a couple of months into the post-harvest season and then quickly dissipates. This type of transitory effect is consistent with the suggested rapacity mechanism, which, moreover, has been alluded to by recent studies (e.g., McGuirk and Burke, 2020). With the identity militias, we observe the elevation of violence in months leading to harvest period. Agro–pastoral conflict could be a possible reason behind the increase of conflict during the lean season, that is, just before the harvest (e.g., McGuirk and Nunn, 2020).

Chart

Description automatically generated

**Figure 3: The seasonal violence by armed groups**

*Note:* the solid lines depict the percent change in violence due to a positive one standard deviation price growth in a location with a cropland area fraction of 0.021, relative to the baseline level of conflict incidence; the shaded regions indicate the two standard deviation confidence intervals of the effect; the dashed lines depict zero.

*Robustness, Sensitivity, and Placebo Tests*

The parameter estimates, reported in Table 3, are robust to different model specifications and data sub-setting. We summarize the robustness and sensitivity checks below. Unless otherwise stated, we present results for violence by political militias, as the estimated coefficients are statistically significant and economically meaningful for this actor.

First, we check that the results are not driven by our choice of the fixed effects. We re-estimate the parameters using different specifications of location and time fixed effects, including country and year fixed effects, as well as country–specific linear trends. We report these parameter estimates in Appendix Table 2. These results are similar, both quantitatively and qualitatively, to the main results of the study.

Second, we ensure the inference is not sensitive to our choice of clustering of the standard errors. We check robustness to clustering at different levels, including a spatial clustering method of Conley (1999). We report these results in Appendix Table 3. The inference from these different methods accords with that applied in the main specification of the study.

Third, we assess parameter constancy over the study period. For this, we re-estimate the parameters using twelve-year partially overlapping subsets of the data starting with the 1997-2008 period and ending with the 2009-2020 period. We illustrate these estimated effects in Appendix Figure 6. While the general pattern of the effects is comparable, we observe a more amplified seasonality and a longer period of the post-harvest violence in the earlier subsets of the data, and more precise, albeit more modest, estimates of the seasonal violence in the more recent subsets of the data.

Fourth, we assess the sensitivity of parameters to omitting observations based on their geographic locations. We re-estimate the parameters by sequentially omitting four geographic bands: the latitudes north of the Tropic of Cancer, the latitudes between the Tropic of Cancer and just north of the equator, the latitudes between just north of the equator and half-way from equator to the Tropic of Capricorn, and the latitudes south of the Tropic of Capricorn (see Appendix Figure 2 for the geographic position of these thresholds). We illustrate these estimated effects in Appendix Figure 7. Overall, we find similar effects, although the main results of the study appear to be strengthened by inclusion of the 22oN–2oN band in the data. This is not surprising, particularly given that in the considered data, the region covers approximately 45 percent of the observed violent events, and 53 percent of cells with cropland.

Fifth, we perform a set of placebo tests where we interchangeably use 6- and 12-month lags and leads of the seasonal price changes in the regression. We present the estimated coefficients from these regressions in Appendix Table 4. None of the estimated parameters are statistically significant at 5% significance level.

Sixth, we test whether there is a dose-response relationship between the intensity of agricultural activities and the seasonal violence. If our conjecture is valid, we would expect greater effect in cells where higher share of land is dedicated to the major crop. For this we introduce a step-function that dichotomizes the croplands into the *very low* agricultural intensity (area fraction of less than 0.7%), *low* agricultural intensity (area fraction between 0.7% and 2.9%), *medium* agricultural intensity (area fraction between 2.9% and 5.5%), and *high* agricultural intensity (area fraction greater than 5.5%). We calculate the percent change in violence by political militias relative to the baseline probability of violence within each agricultural intensity band. We illustrate these estimated effects in Appendix Figure 8. It is evident that the main results of this study are primarily driven by high agricultural intensity locations, likely those with more prominent harvest-related windfalls.

Seventh, we re-estimate the parameters of interest using specification given in equation (1b), that is, while controlling for the cropland area fraction weighted lagged prices interacted with the seasonal dummy variables. We present the parameter estimates for violence by any actor as well as those by each actor in Appendix Table 5. These estimates, by and large, are comparable to those of the main results of the study.

Eight, to confirm that the estimated seasonal pattern is indeed driven by harvest rather than the calendar year seasons, particularly given the anecdotal evidence that wars often happen in late spring and summer the weather conditions are better as to facilitate fighting. For this we re-estimate the parameters using calendar year monthly dummy variables, instead of the crop year seasonal dummy variables, in the regressions. We present the estimates associated with violence by any actor as well as those by each actor in Appendix Table 6. These estimates, by and large, are negligible and not statistically significant.

Finally, we re-estimate the parameters using the UCDP data instead of the ACLED data. We illustrate the estimated effects associated with violence by all actors (as UCDP does not categorize the perpetrators) in Appendix Figure 9. The general pattern of the seasonality observed in the ACLED data is also observed in the UCDP data. Indeed, the estimated effects are more pronounced when the UCDP data are used in the analysis, although the confidence intervals around the point estimates are also wider (likely due to a smaller sample of the data).

*Testing the Plausible Mechanism*

The foregoing checks solidify the main results of this study, which in turn point to rapacity as a plausible mechanism for the seasonal conflict. To test the validity of this mechanism, we interact the original set of independent variables in equation (1) with local weather conditions during the preceding growing season of the main crop in the area. We use exogenous weather, rather than crop yields, as the latter are likely to be endogenous to conflict (e.g., Koren, 2018).

Specifically, we consider two weather variables, the rainfall and temperature. In the case of rainfall, we calculate the cumulative amount of rainfall in a cell during its major crop growing season. In the case of temperature, we calculate the cumulative number of extreme heat days in a cell during the crop growing season. Somewhat arbitrarily, although consistent with the crop production literature, we use 32 degrees Celsius at 2pm as a threshold to determine whether a day is excessively hot. If the data were to support our suggested rapacity mechanism, then during bad harvest years the effect should be less pronounced – less harvest should lead to less conflict, *ceteris paribus*.

Figure 4 illustrates these results, which confirm our hypothesis. Specifically, higher rainfall during the crop growing season, which likely increases the harvest and thus is the source of positive income shock, amplifies the probability of violence after harvest as well as extends the post-harvest period of violence. On the other hand, more extreme heat days during the crop growing season, which likely damages the harvest and thus mitigates the harvest-time income shock, reduces the probability of violence after harvest as well as shrinks the post-harvest period of violence.

**Discussion**

The finding of this study supports the positive income shock mechanism for explaining the seasonality of conflict, and more generally the connection between agricultural production and conflict. This finding is strengthened by the results that show that (i) the effect is less evident after presumably poor harvest, and (ii) it is political militias that are driving the seasonal increase in conflict.

As conflict actors, political militias do not seek to control territory, operate for short periods of time, and have incentives to cause damage to, or to appropriate agricultural surplus from, their opponents or opponents' supporters in order to maximize the relative position of their elite patrons. As such, political militia violence increases during harvest time is in line with expectations about conflict over agricultural surplus being an example of output conflict. In what follows, we further elaborate on this observed pattern of our main finding.

Chart, radar chart

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**Figure 4: Violence by political militias in different growing season weather scenarios.**

*Note:* The graphs illustrate the changes in the incidence of violence by political militias during average climate and excess rainfall (top) or heat days (bottom). The excess rainfall is defined as an additional 214mm (approximately one standard deviation) rainfall during the growing season; the excess heat days is defined as an additional 37 days with at least 32 degrees Celsius during the growing season. The solid lines depict the percent change in violence due to a positive one standard deviation price growth in a location with a cropland area fraction of 0.021, relative to the baseline level of conflict incidence; the shaded regions indicate the two standard deviation confidence intervals of the effect; the dashed lines depict zero.

In thinking about the rapacity mechanism of conflict, temporally, political militias’ violence is better suited to expropriation of short-term production, such as agricultural goods, and the lack of territorial control exercised by political militias means that they are ill-suited to extract income from long-term control over non-seasonal resources such as minerals. Similarly, in thinking about strategic violence designed to harm opponents or decrease opponents’ income, the fact that political militias may operate in the wealthier, more accessible crop-growing areas means that the ability of political militias to harm (civilian) opponents may be served by attacks during harvest time, when the opponents’ income is most prone to disruption. By contrast, rebel groups, who are primarily attacking state forces, would not see any seasonal change in their ability to harm their opponents.

*Seasonality and Attacks on Civilians*

Civilians are attacked during conflicts because they are accessible by conflict actors – either because rebel groups are attempting to open new fronts, because militias are engaging in violence as proxies for state forces (Raleigh, 2012), or because they are facing setbacks in the conflict, and attacks on civilians are acts of desperation (Downes, 2008; Wood & Kathman, 2015). The interaction between rebel groups and the state over control of territory can lead to civilian killings, inasmuch as rebel groups may increase attacks on civilians to contest state consolidation of territorial control (Wood & Sullivan, 2015).

The ebbs and flows of contestation and consolidation of territorial control can lead to increases and decreases in attacks on civilians over time by either the state or rebel groups (Kalyvas, 2006), but unless that contestation perfectly aligns with the growing seasons in different parts of a country, this does not explain seasonality per se. The territoriality of rebel groups may also play a role in a lack of seasonality, inasmuch as they may seize and hold on to territory, and rule it with a variety of institutional arrangements (Mampilly and Stewart, 2021), indicating longer campaigns of violence that may extract resources from the population on a more consistent basis.

While attacks on civilians as retaliation for previous attacks can be seen in the behaviour of all conflict actors, and attacks on civilians in response to the other side’s acquisition of territory can be seen in rebel groups and state forces (Raleigh & Choi, 2017), there is no reason why retaliatory attacks would be seasonal in nature, let alone tied to agricultural production cycles. Political militias are, conditional on engaging in violence, more likely to attack civilians than other types of conflict actors, although they cause fewer fatalities per incident than state forces or rebel groups, suggesting that maximizing casualties is not the goal (or perhaps within the ability) of political militias (Raleigh & Kishi, 2020).

In contrast to many rebel groups, pro-government militias are not attempting to control territory because they are operating in areas that are already controlled (or at least contested) by the state, on behalf of at least one elite actor within the state. Political militias are tools to maximize the power of the elites that control them, and to ‘alter the political landscape,’ including by protecting their own supporters, changing the political landscape, inflicting damage on their opponents, or their opponents’ supporters. Attacks on civilians in this context are useful for inflicting harm on opponents’ followers, to discourage them from supporting the elite opponents (or deter them from attacking the political militia’s own elite patrons) during periods of political contestation (Raleigh, 2016). Using a strategic logic of violence, groups may attempt not only to kill opponents, or damage opposing groups’ ability to fight, but stage attacks for purpose of killing intimidating or their opponents’ supporters, such that the supporters refrain from giving resources to groups (Kydd & Walter, 2006).

Specifically, in developing countries with high dependence on agricultural production, attacking civilians during harvest season can be a useful way of damaging opponents' support base when they are at their most vulnerable – the time of the year when they are (in theory) realizing the bulk of their income for the year. Opponents’ supporters may lose income from the loss of agricultural products directly or through disruption of the harvest. As such, political militias can benefit their patrons by shifting the political landscape to decrease the resources available to, and patronage of, their patrons' opponents. In this understanding, whether the political militias directly profit from appropriating agricultural production during the harvest season is less material than whether their opponents lose income and supporters.

*Seasonality and Income Generation*

Conflict actors must also sustain themselves financially, regardless of whether the conflict is motivated by a desire for income or a grievance against the state or other opponents (Collier & Hoeffler, 2004). Violence against civilians may arise as a result of opportunities for ‘looting’, not only of mineral resources (Azam & Hoeffler, 2002; Rigterink, 2020), but also of agricultural products. This could be because the government and rebels are competing for control of food (Koren & Bagozzi, 2017), or because, in straitened times, civilians and violent groups fight over attempts at predation (Bagozzi, Koren, & Mukherjee, 2017).

What may differ is how the conflict actors generate income. State forces by definition control territory, and (in theory) extract income by taxing economic activity in that territory. Control of territory also allows rebel groups to extract income, due to natural resource exploitation or, if the rebel group has sufficient capacity, taxation of the civilian population (Beardsley, Gleditsch, & Lo, 2015; Conrad et al., 2019; Lujala, 2010; Mampilly, 2011). However, neither natural resource exploitation nor taxation *per se* is necessarily seasonal in nature: groups engaged in factor conflict should see no systematic increase or decrease associated with the harvest season.

Unlike states or rebel groups, the goal of political militia violence is not to operate, and collect income, over an extended period of time. Indeed, because the purpose of political militia violence is to aid elites in fighting for positions within the state, political militias are likely to be short-lived, and to engage in attacks in territory that that their elite patrons (or more generally the state) already control (Choi & Raleigh, 2021; Raleigh, 2014). In addition, unlike rebel groups or identity militias, political militias are not marginalized relative to the resources or power structures of the state. If they are to be consistently loyal to one set of elites (or the state in general), they also need to be paid, either directly, or through patronage, or exploitation opportunities against their opponents or opponents’ supporters.

As such, political militias, as groups that are not attempting to control territory in order to extract long-term income, are more likely to be engaging in output conflict. If political militias are engaging in attacks on civilians as a short-term means of extracting income from them, particularly through the appropriation of agricultural surplus, or attacking civilians as a means of decreasing their income, and thus their ability to support opposing elites (or to more generally degrade the political position of the opposing elites), then that would explain why they would increase their violence during harvest time in crop-producing regions.

**Conclusion**

The relationship between climate and conflict has attracted a large literature (e.g., Buhaug et al. 2015; Harari & Ferrara, 2018; Vestby 2019; von Uexkull & Buhaug, 2021), although the actual pathway in this relationship is often indirect or ambiguous. One of these potential pathways are shocks in agricultural production (e.g., Koren, 2018). Using monthly data on violence against civilians, as well as international prices for locally produced major cereals, we show that short–term farm income windfalls can amplify conflict in the cropland of Africa.

By investigating the seasonal pattern of violence in Africa, we illustrate that commodity price shocks fuel conflict in croplands during the postharvest period, plausibly as a result of increased attempts to appropriate surplus during this period. The most visible aggressors in this instance are political militias, whose motivation is to appropriate agricultural outputs for income, and to disrupt the income of their opponents and opponents’ supporters. This effect—which is most evident during the first three months immediately after harvests—is statistically significant and remains robust to alternative model specification and data sub-setting.

That farm income can fuel violence in conflict–affected states, has been documented in the most recent literature (e.g., Koren, 2018; McGuirk and Burke, 2020). Our study adds an important nuance to this relationship by linking conflict occurrence with the timing of agricultural windfalls, which varies across Africa due to geo-climatic peculiarities of crop production. Furthermore, we separately study the involvement of different perpetrators in violent acts against civilians. We find that overwhelmingly, the connection between agricultural income shocks and violence comes from an increase in attacks by militias connected to political elites during intra-regime contestation. This violence by political militias, which can be strategic, may intensify during harvest times because this is when political militias can maximize their opportunities for appropriation of agricultural products, as well as do the most damage to their opponents and opponents’ supporters, thus shifting the political landscape in favour of their elite patrons.

This new finding matters, as it points to a likely temporal displacement of agricultural income–related conflict in the cropland of Africa. This can help more effective planning by local or international parties toward mitigating conflict or avoiding ambush when operating in conflict–prone regions. Notably, because the perpetrators of harvest season-related conflict are likely to be political militias connected to at least one elite faction within the state, parties seeking to mitigate conflict would need to take this into account when dealing with the state.

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**Appendix Tables**

**Appendix Table 1: Characteristics of different types of conflict actors**

|  |  |  |  |
| --- | --- | --- | --- |
|  | *Territorial control*  *and contestation* | *Timing of violence* | *Location of violence* |
| *State forces* | Yes | Long-term | Areas included within state institutions, areas contested with rebel forces |
| *Rebel groups* | Yes | Long-term | Areas discriminated against by state institutions |
| *Political militias* | No | Short-term | Areas included within state institutions |
| *Identity militias* | No | Short-term | ‘Ungoverned’, peripheral areas |

**Appendix Table 2: Robustness to fixed effects**

|  |  |  |  |
| --- | --- | --- | --- |
|  | (1) | (2) | (3) |
| *Variables* |  |  |  |
| shock×d0 | 0.287\*\* | 0.298\*\* | 0.193 |
|  | (0.135) | (0.137) | (0.118) |
| shock×d1 | 0.292\*\* | 0.307\*\* | 0.232\*\*\* |
|  | (0.129) | (0.133) | (0.086) |
| shock×d2 | 0.207\* | 0.218\* | 0.128 |
|  | (0.113) | (0.115) | (0.106) |
| shock×d3 | -0.041 | -0.032 | -0.065 |
|  | (0.087) | (0.087) | (0.075) |
| shock×d4 | -0.031 | -0.024 | -0.060 |
|  | (0.072) | (0.073) | (0.062) |
| shock×d5 | -0.106 | -0.102 | -0.105 |
|  | (0.080) | (0.081) | (0.077) |
| shock×d6 | -0.038 | -0.038 | -0.033 |
|  | (0.082) | (0.082) | (0.074) |
| shock×d7 | -0.023 | -0.019 | -0.010 |
|  | (0.072) | (0.073) | (0.065) |
| shock×d8 | 0.051 | 0.053 | 0.068 |
|  | (0.075) | (0.076) | (0.068) |
| shock×d9 | -0.027 | -0.021 | 0.029 |
|  | (0.067) | (0.067) | (0.061) |
| shock×d10 | 0.144 | 0.141 | 0.192\* |
|  | (0.092) | (0.094) | (0.101) |
| shock×d11 | 0.053 | 0.065 | 0.016 |
|  | (0.088) | (0.088) | (0.084) |
| *Controls* |  |  |  |
| Cell FE | Y | Y | Y |
| Year FE | Y |  |  |
| Year-month FE |  | Y |  |
| Country-trend |  |  | Y |
| ln(population) | Y | Y | Y |

*Note:* the dependent variable is a binary variable that depicts the incidence of political violence; shock is the annual growth of the price for the major crop in a cell interacted with the cropland area fraction in the cell; dh is the crop year binary seasonal variable where *h* depicts months from harvest, so that the subscript *0* depicts the harvest month, the subscript *1* depicts the next month after harvest, and so forth until subscript *11* that depicts the 11th month after harvest which is also, by default, the month just before harvest; all regressions include cell fixed effects and control for log(population), they also include year or year-month fixed effects, or control for country-specific trends; the values in parentheses are standard errors adjusted to clustering at the level of a grid-cell and a country-year; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels.

**Appendix Table 3: Robustness to clustering**

|  |  |  |  |
| --- | --- | --- | --- |
|  | (1) | (2) | (3) |
| *Variables* |  |  |  |
| shock×d0 | 0.224\*\* | 0.224\*\* | 0.224\* |
|  | (0.090) | (0.112) | (0.120) |
| shock×d1 | 0.203\*\*\* | 0.203\*\*\* | 0.203\*\*\* |
|  | (0.064) | (0.061) | (0.068) |
| shock×d2 | 0.107 | 0.107 | 0.107 |
|  | (0.079) | (0.085) | (0.081) |
| shock×d3 | -0.061 | -0.061 | -0.061 |
|  | (0.063) | (0.073) | (0.076) |
| shock×d4 | -0.030 | -0.030 | -0.030 |
|  | (0.057) | (0.052) | (0.060) |
| shock×d5 | -0.095 | -0.095 | -0.095 |
|  | (0.064) | (0.062) | (0.075) |
| shock×d6 | -0.018 | -0.018 | -0.018 |
|  | (0.063) | (0.070) | (0.077) |
| shock×d7 | -0.007 | -0.007 | -0.007 |
|  | (0.041) | (0.043) | (0.028) |
| shock×d8 | 0.057 | 0.057 | 0.057 |
|  | (0.064) | (0.071) | (0.058) |
| shock×d9 | -0.027 | -0.027 | -0.027 |
|  | (0.048) | (0.047) | (0.050) |
| shock×d10 | 0.133 | 0.133 | 0.133 |
|  | (0.089) | (0.091) | (0.091) |
| shock×d11 | 0.011 | 0.011 | 0.011 |
|  | (0.067) | (0.067) | (0.072) |
| *Controls* |  |  |  |
| Cell FE | Y | Y | Y |
| Country-year FE | Y | Y | Y |
| ln(population) | Y | Y | Y |
| *Clustering* |  |  |  |
| Cell | Y |  |  |
| Latitude |  | Y |  |
| Conley (500km) |  |  | Y |

*Note:* the dependent variable is a binary variable that depicts the incidence of political violence; shock is the annual growth of the price for the major crop in a cell interacted with the cropland area fraction in the cell; dh is the crop year binary seasonal variable where *h* depicts months from harvest, so that the subscript *0* depicts the harvest month, the subscript *1* depicts the next month after harvest, and so forth until subscript *11* that depicts the 11th month after harvest which is also, by default, the month just before harvest; all regressions include cell and country-year fixed effects, and control for log(population); the values in parentheses are standard errors adjusted to clustering at the level of a grid-cell, latitude, or as per Conley (1999) using 500km cut-off; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels.

**Appendix Table 4: Placebo tests using lags and leads of income shocks**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Lags** | | **Leads** | |
|  | *12 months* | *6 months* | *6 months* | *12 months* |
| *Variables* |  |  |  |  |
| shock×d0 | -0.013 | 0.029 | -0.122\* | -0.034 |
|  | (0.070) | (0.053) | (0.068) | (0.101) |
| shock×d1 | 0.133 | 0.124\* | 0.094 | -0.051 |
|  | (0.094) | (0.069) | (0.069) | (0.104) |
| shock×d2 | 0.028 | 0.034 | 0.060 | -0.120 |
|  | (0.085) | (0.065) | (0.071) | (0.104) |
| shock×d3 | -0.013 | 0.046 | -0.070 | 0.010 |
|  | (0.091) | (0.082) | (0.082) | (0.075) |
| shock×d4 | 0.050 | 0.038 | -0.094 | -0.074 |
|  | (0.067) | (0.072) | (0.074) | (0.072) |
| shock×d5 | -0.070 | -0.128\* | -0.087 | -0.172\* |
|  | (0.069) | (0.070) | (0.075) | (0.094) |
| shock×d6 | -0.091 | -0.133 | 0.018 | 0.047 |
|  | (0.069) | (0.104) | (0.076) | (0.110) |
| shock×d7 | -0.058 | -0.099 | 0.002 | 0.052 |
|  | (0.054) | (0.074) | (0.074) | (0.060) |
| shock×d8 | 0.064 | 0.069 | 0.109 | -0.081 |
|  | (0.067) | (0.074) | (0.096) | (0.062) |
| shock×d9 | 0.045 | 0.034 | -0.098 | -0.068 |
|  | (0.080) | (0.07) | (0.062) | (0.055) |
| shock×d10 | -0.043 | 0.056 | 0.042 | -0.041 |
|  | (0.083) | (0.067) | (0.079) | (0.078) |
| shock×d11 | 0.070 | -0.069 | -0.004 | 0.010 |
|  | (0.101) | (0.075) | (0.095) | (0.095) |
| *Controls* |  |  |  |  |
| Cell FE | Y | Y | Y | Y |
| Country-year FE | Y | Y | Y | Y |
| ln(population) | Y | Y | Y | Y |

*Note:* the dependent variable is a binary variable that depicts the incidence of political violence; shock is the 12- and 6-month lag or lead of the annual growth of the price for the major crop in a grid cell; dh is the crop year binary seasonal variable where *h* depicts the month after harvest; all regressions control for log(population); the values in parentheses are standard errors adjusted to clustering at the level of a grid-cell and a country-year; \* denotes 0.10 statistical significance level.

**Appendix Table 5: Impacts effect while controlling for long-run effects**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Violence by | Violence disaggregated by: | | | |
|  | All actors | State  forces | Rebel  groups | Political militias | Identity militias |
| *Variables* |  |  |  |  |  |
| shock×d0 | 0.224\* | -0.063 | -0.026 | 0.282\*\* | 0.074\*\* |
|  | (0.118) | (0.065) | (0.043) | (0.112) | (0.033) |
| shock×d1 | 0.264\*\* | -0.025 | 0.019 | 0.240\*\*\* | 0.018 |
|  | (0.105) | (0.060) | (0.044) | (0.078) | (0.036) |
| shock×d2 | 0.173 | -0.036 | 0.035 | 0.157\* | 0.034 |
|  | (0.114) | (0.065) | (0.036) | (0.094) | (0.044) |
| shock×d3 | -0.189\* | -0.042 | -0.020 | -0.028 | -0.018 |
|  | (0.106) | (0.067) | (0.045) | (0.086) | (0.031) |
| shock×d4 | 0.075 | 0.088 | -0.046 | 0.061 | 0.016 |
|  | (0.129) | (0.072) | (0.046) | (0.067) | (0.048) |
| shock×d5 | -0.124 | -0.078 | -0.100\*\* | -0.050 | 0.038 |
|  | (0.094) | (0.059) | (0.046) | (0.074) | (0.038) |
| shock×d6 | -0.007 | 0.036 | -0.065\* | 0.025 | 0.011 |
|  | (0.124) | (0.051) | (0.040) | (0.073) | (0.08) |
| shock×d7 | 0.033 | 0.083 | -0.029 | -0.009 | 0.057 |
|  | (0.097) | (0.059) | (0.043) | (0.061) | (0.058) |
| shock×d8 | 0.101 | 0.030 | -0.041 | 0.129 | 0.015 |
|  | (0.086) | (0.039) | (0.038) | (0.081) | (0.033) |
| shock×d9 | 0.067 | 0.039 | -0.046 | 0.032 | -0.018 |
|  | (0.097) | (0.066) | (0.047) | (0.066) | (0.039) |
| shock×d10 | 0.148 | 0.019 | -0.035 | 0.175 | 0.062 |
|  | (0.116) | (0.042) | (0.040) | (0.108) | (0.045) |
| shock×d11 | 0.074 | -0.009 | -0.040 | 0.055 | 0.086 |
|  | (0.114) | (0.069) | (0.038) | (0.091) | (0.058) |
| *Controls* |  |  |  |  |  |
| Cell FE | Y | Y | Y | Y | Y |
| Country-year FE | Y | Y | Y | Y | Y |
| ln(population) | Y | Y | Y | Y | Y |
| Lagged prices ×  crop year seasons | Y | Y | Y | Y | Y |

*Note:* the dependent variable is a binary variable that depicts the incidence of political violence; shock is the annual growth of the price for the major crop in a cell interacted with the cropland area fraction in the cell; dh is the crop year binary seasonal variable where *h* depicts the month after harvest; all regressions include cell and country-year fixed effects, and control for log(population); all regressions also include lagged prices interacted with cropland area fractions and crop year binary seasonal variables, as illustrated in equation (1b); the values in parentheses are standard errors adjusted to clustering at the level of a grid-cell and a country-year; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels.

**Appendix Table 6: Calendar year seasonality of violence due to income shocks**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Violence by | Violence disaggregated by: | | | |
|  | All actors | State  forces | Rebel  groups | Political militias | Identity militias |
| *Variables* |  |  |  |  |  |
| shock×m1 | -0.119 | -0.109 | 0.014 | 0.040 | 0.017 |
|  | (0.100) | (0.081) | (0.055) | (0.080) | (0.034) |
| shock×m2 | 0.075 | 0.048 | 0.037 | -0.030 | 0.026 |
|  | (0.100) | (0.056) | (0.034) | (0.051) | (0.046) |
| shock×m3 | 0.112 | 0.057\*\* | 0.022 | 0.017 | 0.051\* |
|  | (0.084) | (0.023) | (0.032) | (0.076) | (0.029) |
| shock×m4 | -0.037 | 0.037 | -0.035 | 0.002 | 0.026 |
|  | (0.096) | (0.046) | (0.039) | (0.064) | (0.055) |
| shock×m5 | 0.104 | -0.006 | 0.023 | 0.062 | 0.037 |
|  | (0.079) | (0.057) | (0.034) | (0.064) | (0.044) |
| shock×m6 | -0.018 | -0.069 | 0.041 | -0.007 | 0.017 |
|  | (0.071) | (0.042) | (0.028) | (0.052) | (0.033) |
| shock×m7 | 0.029 | -0.045 | -0.011 | 0.042 | 0.013 |
|  | (0.084) | (0.040) | (0.050) | (0.057) | (0.030) |
| shock×m8 | 0.029 | -0.156\*\* | 0.012 | 0.097 | 0.087\* |
|  | (0.100) | (0.075) | (0.040) | (0.066) | (0.048) |
| shock×m9 | -0.127 | -0.091 | -0.018 | -0.004 | 0.029 |
|  | (0.126) | (0.061) | (0.049) | (0.094) | (0.035) |
| shock×m10 | 0.041 | -0.124\* | -0.033 | 0.123 | 0.003 |
|  | (0.126) | (0.073) | (0.052) | (0.095) | (0.031) |
| shock×m11 | 0.037 | 0.001 | -0.053 | 0.091 | -0.001 |
|  | (0.097) | (0.068) | (0.046) | (0.075) | (0.049) |
| shock×m12 | 0.151 | -0.048 | 0.007 | 0.109 | 0.064\* |
|  | (0.109) | (0.062) | (0.044) | (0.084) | (0.038) |
| *Controls* |  |  |  |  |  |
| Cell FE | Y | Y | Y | Y | Y |
| Country-year FE | Y | Y | Y | Y | Y |
| ln(population) | Y | Y | Y | Y | Y |

*Note:* the dependent variable is a binary variable that depicts the incidence of political violence; shock is the annual growth of the price for the major crop in a cell interacted with the cropland area fraction in the cell; mj is the monthly binary variable where *j* depicts the calendar year month; all regressions include cell and country-year fixed effects, and control for log(population); the values in parentheses are standard errors adjusted to clustering at the level of a grid-cell and a country-year; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels.

**Appendix Figures**

Chart

Description automatically generated

**Appendix Figure 1: The country ranking by conflict prevalence**

*Note:* The values in parentheses, next to the country/territory names, indicate the number of grid cells within the country/territory with at least one conflict incident over 1997–2020 period.

Map

Description automatically generated

**Appendix Figure 2: Geographic density of population across Africa**

*Note:* Grid cells with 2020 population of at least 50 thousand are presented. The values are in millions.

Chart

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**Appendix Figure 3: Harvest seasons by country and crop**

*Note:* The lines capture the length of the crop harvest season; the points denote the mid-point month of the harvest season. The line thickness is proportional to the number of grid cells with a given crop in the country. The line transparency is inversely proportional to the average fraction of the cropland in grid cells of a country.

Chart

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**Appendix Figure 4: Growing seasons by country and crop**

*Note:* The lines capture the length of the crop growing season defined as the period between the mid-point months of the planting and harvest seasons. The line thickness is proportional to the number of grid cells with a given crop in the country. The line transparency is inversely proportional to the average fraction of the cropland in grid cells of a country.

**Chart, bar chart

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**Appendix Figure 5: Distribution of grid-cells by fraction of cropland area**

Radar chart

Description automatically generated with medium confidence

**Appendix Figure 6: Parameter sensitivity to timeframe covered in the analysis**

*Note:* the solid lines depict the percent change in violence due to a positive one standard deviation price growth in a location with a cropland area fraction of 0.021, relative to the baseline level of conflict incidence, during the considered timeframe; the shaded regions indicate the two standard deviation confidence intervals of the effect; the dashed lines depict zero.

Chart

Description automatically generated

**Appendix Figure 7: Parameter sensitivity to omitted latitudes**

*Note:* the solid lines depict the percent change in violence due to a positive one standard deviation price growth in a location with a cropland area fraction of 0.021, relative to the baseline level of conflict incidence, across the considered latitudes; the shaded regions indicate the two standard deviation confidence intervals of the effect; the dashed lines depict zero.

A picture containing text, electronics

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**Appendix Figure 8: Dose-response relationship**

*Note:* the solid lines depict the percent change in violence due to a positive one standard deviation price growth relative to the baseline level of conflict incidence, within the considered cropland intensity bands; of the considered croplands, 0.007 is approximately the 50th percentile area fraction, 0.029 is approximately the 80th percentile area fraction, and 0.055 is approximately the 90th percentile area fraction; the shaded regions indicate the two standard deviation confidence intervals of the effect; the dashed lines depict zero.

Chart, radar chart

Description automatically generated

**Appendix Figure 9: Sensitivity of results to different sources of conflict data**

*Note:* the solid lines depict the percent change in violence due to a positive one standard deviation price growth in a location with a cropland area fraction of 0.021, relative to the baseline level of conflict incidence; the shaded regions indicate the two standard deviation confidence intervals of the effect; the dashed lines depict zero. The ACLED estimates are based on a total of 55,942 events that comprise 24,598 cell–month observations with at least one event; the baseline incidence of violence in cells with some cropland is 0.046. The UCDP estimates are based on a total of 9,362 events that comprise 5,106 cell-month observations with at least one event; the baseline incidence of violence in cells with some cropland is 0.007.

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2. As a robustness check, we also use data on conflict from the Uppsala Conflict Data Program (UCDP) Georeferenced Event Dataset (global version 21.1), available at https://ucdp.uu.se. We briefly discuss these data in the *Auxiliary Data* subsection below. [↑](#footnote-ref-2)
3. An alternative interpretation of this coefficient is that it is an impact effect of a price change. To illustrate the point, consider an augmented version of equation (1) given by:

   (1a)

   Note that equation (1) is the restricted case of equation (1’), where coefficients , h=0,…,11 are impact effects, and are the long-run effects of cropland area-weighted price changes on conflict incidence. Denote the long-run coefficient, express in terms of and , and substitute it in equation (1’). A simple algebraic manipulation will yield:

   (1b)

   While our main specification is that expressed by equation (1), we also estimate equation (1b) in our suite of robustness checks. [↑](#footnote-ref-3)