Commodity Price Shocks and the Seasonality of Conflict

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Abstract

Commodity price shocks can exacerbate conflict in low income countries with weak institutions. In these countries, agriculture usually is a key source of employment and income. A unique feature of agricultural income is its seasonality, which manifests in harvest-time windfalls. Conflict, therefore, can be seasonal as well. We combine temporal variation in international cereal prices at monthly frequency with spatial variation in cereal crop production and harvest seasons at the one-degree grid cell level to investigate the effect of year–on–year growth in cereal prices on conflict across Africa. We find that in the cropland, conflict is more likely during the first three months after a harvest, when the expected value of spoils to be appropriated is highest. During this period, a one–standard–deviation increase in prices can result in a more than three–percent increase in conflict incidents. We also find that among potential perpetrators, political militias are the most likely culprits behind seasonal conflict in the cropland of Africa. This study offers an important nuance to the growing literature aimed at investigating the economic causes of conflict in fragile states with weak institutions.

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

JEL Codes: D74; O13; Q02.

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1 Introduction

In low–income economies with weak institutions, where some deviations from law and order are more of a norm than an exception, a change in people's income may exacerbate the whole range of unlawful activities. Bad harvests or drops in crop prices can be important sources of income shocks in regions where agriculture is an integral part of the economy. Indeed, empirical evidence points to a strong linkage between crop yields and conflict (Buhaug et al., 2015; Koren and Bagozzi, 2017; Koren, 2018), as well as commodity prices and conflict (Berman and Couttenier, 2015; Fjelde, 2015; Crost and Felter, 2020; McGuirk and Burke, 2020).

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 marketing year as well as the abrupt influx of income shortly after harvests, is likely to also have a seasonal pattern. The former lends itself well to the opportunity cost mechanism of conflict in 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.

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 (Dube and Vargas, 2013), which in agricultural sector is likely to 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 marketing 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 examining the relationship between agricultural income shocks and conflict, 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, more recently, at the grid cell level (e.g., Fjelde, 2015; Berman and Couttenier, 2015; Berman et al., 2017; Koren, 2018). These yearly estimations represent the average effect and may conceal important seasonal patterns. The few studies that have worked with monthly data, have not specifically examined 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.

We study the seasonal effect of agricultural income shocks on conflict by examining 24 years of monthly data covering 2538 one-degree grid cells across 51 African economies where agriculture is the key source of income, and where conflicts, by and large, are part of daily life. Our empirical strategy is akin to a difference–in–differences approach that combines movements in global cereal crop prices with geographic variation in crop production and harvest seasons.

Our study presents compelling evidence of the seasonality of conflict. We find that a positive agricultural income shock increases conflict early in the postharvest period; the effect vanishes as the marketing year progresses. We also find that, among potential perpetrators, the most likely culprits are *political militias*, which specialize in extorting short–term income, unlike other, more organized and perhaps better funded military groups, such as state forces.

In our main contribution to the literature, we examine and find the seasonal pattern of conflict, plausibly linked with changes in agricultural income due to exogenous price shocks and harvest–related windfalls, in the cropland of Africa. That farm income can fuel violence in conflict–affected states, has been documented in the most recent literature (Koren, 2018; McGuirk and Burke, 2020). Here, we present an important nuance to this relationship by linking the conflict occurrence with the seasonality of farm income. The finding is economically meaningful, as it suggests a likely income–related temporal displacement of conflict in the cropland of Africa.

2 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 casual altercations among neighbors 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.

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' does not 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 rebel groups and militias living off the land (e.g., Koren and Bagozzi, 2017).

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, 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 military 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 farms and burning houses, foodstuffs, and personal belongings.

3 Data

We apply publicly available data on civil unrest, cereal crop harvest, and cereal crop prices, obtained 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, 1426 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.

3.1 Conflict

We obtain the data on conflict from the ACLED Project (Raleigh et al., 2010), available at https://acleddata.com/. The current version of the dataset groups events into six categories. Of these, we use events categorized as 'violence against civilians.' 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, because not all reported incidents are measured with precision, we discard events with geo-precision code 3, which assigns a conflict to a provincial capital, to avoid adding measurement error to the data. We maintain all time-precision levels, as the least accurate code in the database still gives the correct month. As a result, we analyze a total of 55,486 unique incidents that occurred between January 1997 and December 2020 across 51 countries/territories in Africa. Figure 1 ranks these countries by conflict prevalence over the study period.

ACLED Project aggregates actors into four distinct categories (Raleigh et al., 2010). These are *state forces*, *rebel groups*, *political militias*, and *identity militias*. 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 counter a ruling regime, typically by means of violent acts. 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. Figure 2 illustrates the geographical distribution and prevalence of the selected conflict incidents by actor type across Africa.

While the reported incidents cover most of the populous parts of the continent (the population map is presented in Appendix Figure F1), 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 are, by far, the most prevalent set of actors that appear across all of Africa. Rebel groups and identity militias are endemic to the equatorial part of Africa, but there appears a limited geographic overlap between the two groups.

3.2 Cereal Crops and Prices

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. We consider four cereal crops: maize, sorghum, wheat, and rice. For each of these crops, we obtain the fraction

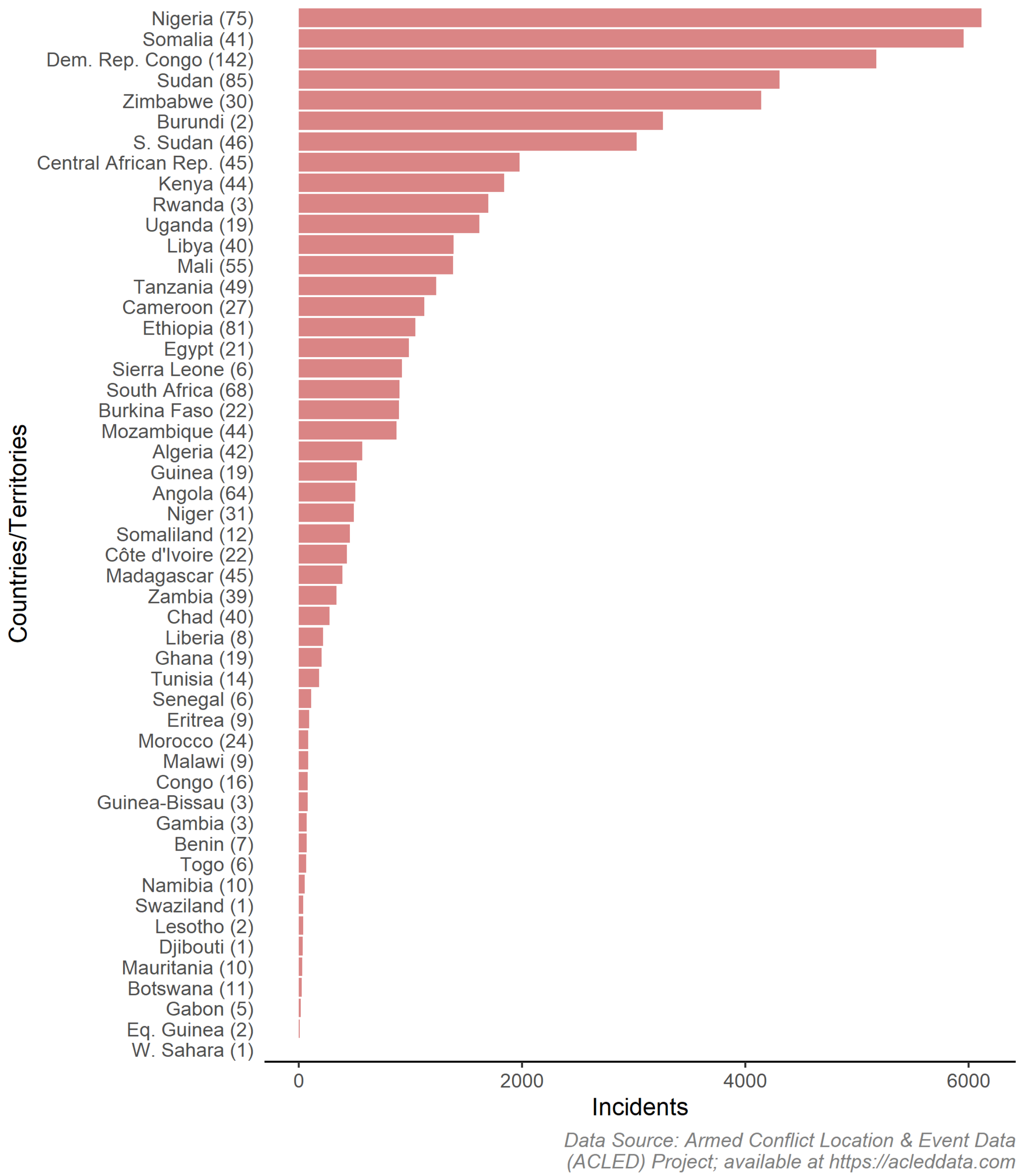

Figure 1: Country ranking by conflict prevalence

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.

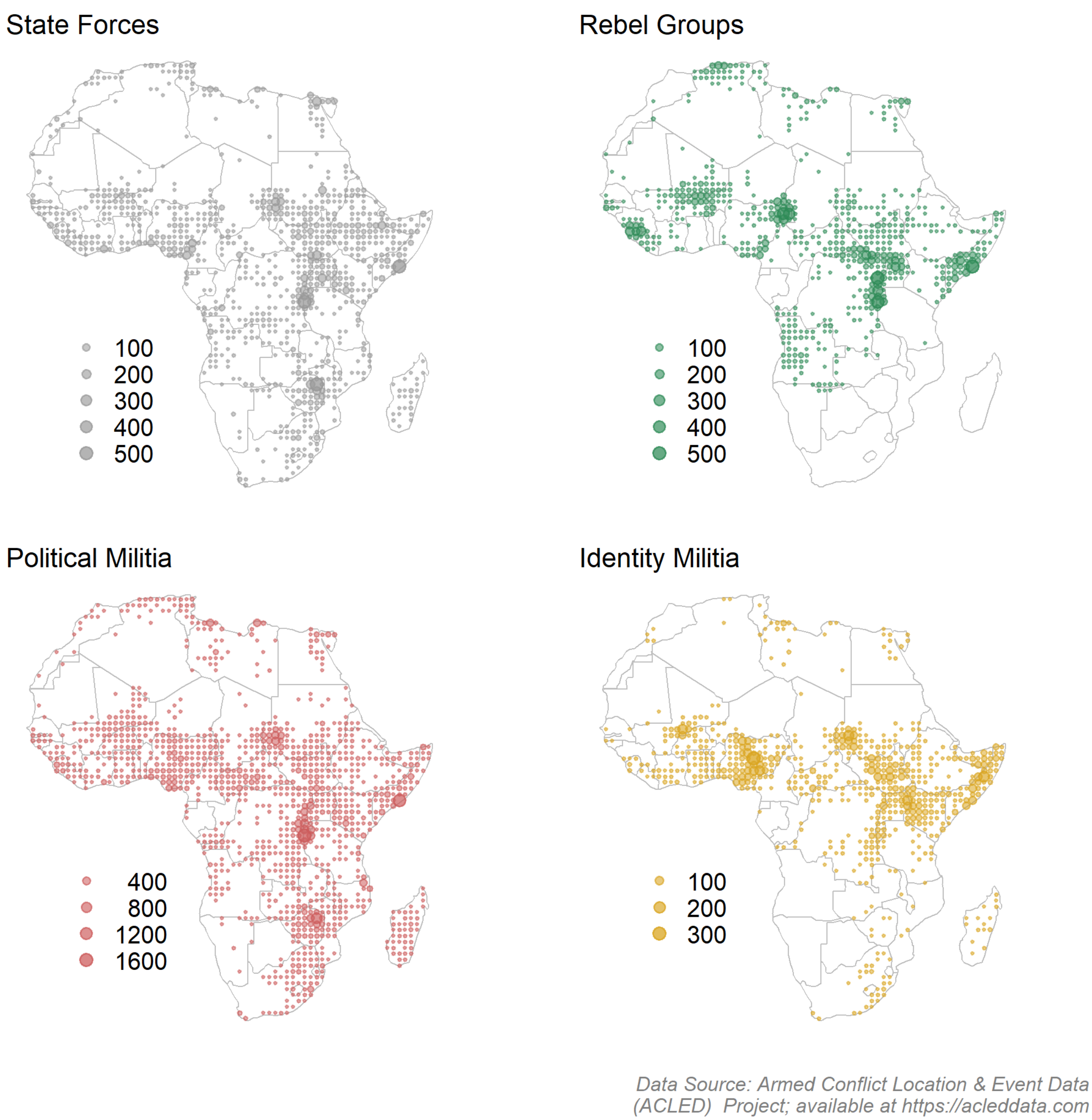

Figure 2: Conflict by actors across space

Note: Grid cells with at least one incident over 1997-2020 period are presented. The values are the total number of incidents in a grid cell during the study period.

of the harvested area within a grid cell. In a multi-crop grid cell, we consider the major crop as that with the largest fraction of the harvested area. We obtain the harvest month for the major crop in each grid cell. These remain fixed over the study period.

We source commodity price data from the International Monetary Fund (IMF), available at 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. Figure 3 illustrates the geographical distribution of locations across Africa where each of the four cereal crops are the most prevalent (see Appendix Figure F2 for the harvest months of the major crop across Africa), and the time series of the associated prices.

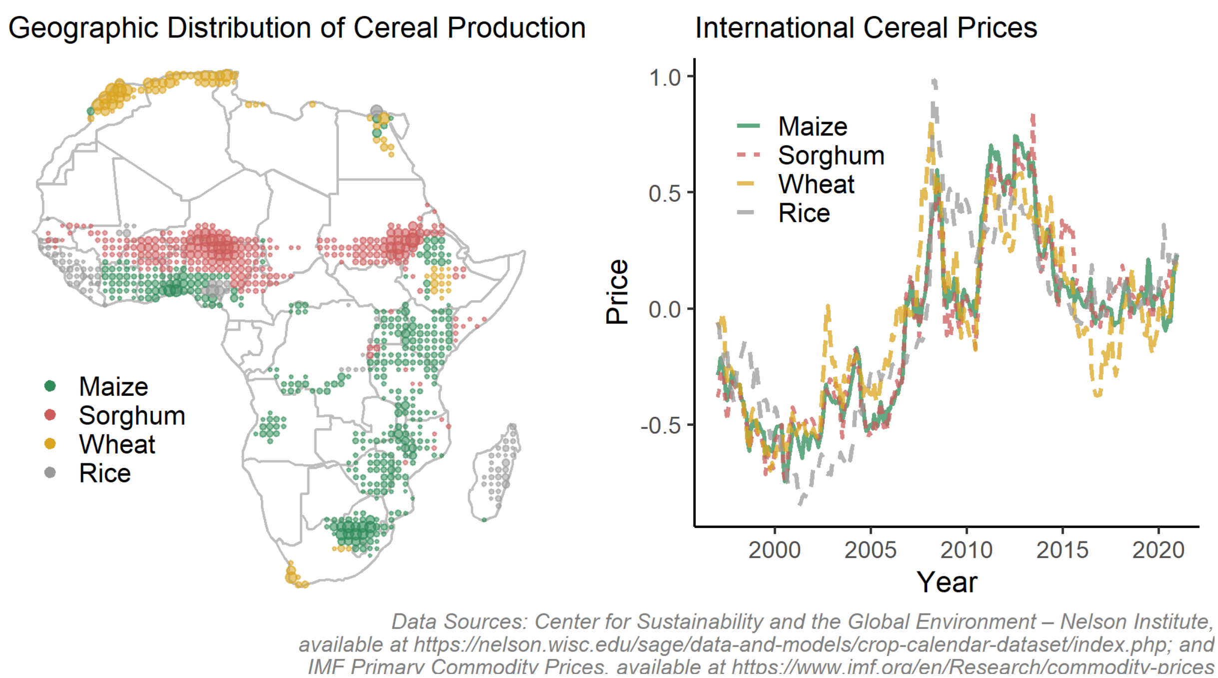

Figure 3: Major cereal crops across space and their prices over time
Note: Grid cells with at least 0.01 share of cropland are presented. Prices are mean–centered and log–transformed for illustrative convenience.

3.3 Other 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.

Population estimates are available for 2000, 2005, 2010, 2015, and 2020. Using these estimates, we interpolate the population data for all other years in the 1997–2020 range, using a cubic spline method. We use these population estimates to obtain per capita conflict incidents, and to weight observations in the regression analysis.

4 Empirical Strategy

In what follows, we denote a grid cell observation with subscript i (henceforth also referred to as a *location*), and a year–month with subscript t (henceforth also referred to as a *period*). The econometric specification is as follows:

$$\text{conflict}_{it} = \sum_{j=0}^{11} \beta_j \text{shock}_{it} \times \text{harvest}_{im+j} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where conflict_{it} denotes the number of conflict incidents per million population in location i during period t; $\text{shock}_{it} = \Delta_{12} p_{it} c_i$ is the *agricultural income shock*, where $\Delta_{12} p_{it} = p_{it} - p_{it-12}$ is the annual growth in price for the major crop in grid cell i, and $c_i = I(s_i \geq 0.01)$, where s_i share of harvested area in the grid cell, and $I(\cdot)$ is the Heaviside indicator function that takes on one when the condition within the parenthesis is satisfied and zero otherwise;[1] $\text{harvest}_{im+j} : j = 0, \ldots, 11$ are location–specific seasonal dummy variables, which are different across locations due to differences in climatic conditions and the specificity of growing conditions for the most prevalent crop in each location. The seasonal dummy variables thus correspond to a marketing year rather than a calendar year, with harvest_{im} denoting the harvest month, and $\text{harvest}_{im+j},\ j = 1, \ldots, 11$ denoting all subsequent months of the marketing year. μ_i and λ_t are grid cell and year–month fixed effects; and ε_{it} is an error term.

In principle, the direction of causality can go both ways in the income–conflict relationship. Thus, to avoid the issue of reverse causality, we use international prices, which are unlikely to be affected by conflict in Africa (see also Bazzi and Blattman, 2014; McGuirk and Burke, 2020), and we maintain the harvest area and harvest month fixed for each grid cell, which mitigates

[1] As a robustness check, we vary the threshold, and re-estimate parameters for thresholds 0.005 and 0.02. The results of this exercise are displayed in the Appendix Tables T3 and T4.

instances when conflict may have caused changes in crop production or harvest timing. Indeed, an identifying assumption in equation (1) is that across different locations the international price change over time is exogenous to conflict observed in these locations, conditional on geographic fixed effects that capture any time–invariant determinants of conflict (e.g., distance to roads, cities, or state borders), and year–month fixed effects that capture common shocks, as well as possible changes in the quality of the data collection/reporting over time. Note that harvest months vary across space (see Figure F2), because of different geo–climatic conditions as well as varying growing seasons of the most harvested cereal crop in a location.

The estimated coefficient, β_j, reflects the effect of a change in shock_{it} on the change in conflict per million people in a given month of the marketing year. For example, a positive value of the coefficient implies that growth in the crop price is associated with a relative increase in conflict incidents in that month of the harvesting year in the affected cropland vs. rest of the locations. This coefficient can be interpreted as the causal effect under the assumptions outlined above.

5 Results

Table 1 presents the main results of this study. The first column of the table includes parameter estimates associated with conflict by any actor. There may be heterogeneity in the ways different actors may contribute to conflict, however. To investigate which of the actors are the most likely perpetrators of conflict, we re-estimate equation (1) for the subsets of data where only incidents pertinent to each of the four military groups, as described above, are recorded. Columns two through five of the table include parameter estimates associated with each of the four armed groups.

There is evidence of a considerable increase in conflict during the first three months of the marketing year. To provide some context, the parameter estimate of 1.19—the coefficient associated with the first month after the harvest period—translates to a nearly 13 percent increase in conflict per million people, relative to the baseline measure for the same period across all the cropland, in response to a 25 percent (approximately one standard deviation of the observed variation) annual growth in prices. This finding corroborates that of Koren (2018) who found that conditional on average conflict in a locality, conflicts arise more often during years with high yields.

We also observe the elevation of conflict incidents in months leading to harvest period. There can be two explanations to this. First, the harvest season can start at earlier period than the expected harvest month. Second, the agro–pastoral conflict can be a reason behind the increase of conflict during the lean season (McGuirk and Nunn, 2020).

When we assess the effect of agricultural income shocks across different military groups, the evidence points to *political militias* as the dominant actor contributing to violence in the agricultural regions of Africa, particularly as it relates to the seasonality of conflict. Conflict associated with rebel groups and identity militia manifests somewhat uniformly throughout the marketing year.

5.1 Robustness Checks

The parameter estimates of the main specification are robust to data subsetting and different model specifications. Appendix Table T1 replicates the main results while varying the fixed effects. Specifically, we consider different combinations of location and time fixed effects, including country and year fixed effects, as well as country–specific linear trends. These results are similar, both quantitatively and qualitatively, to the main results presented in Table 1.

Appendix Table T2 presents parameter estimates from regressions applied on subsets of the data. Specifically, we re-estimate the parameters using data on locations in sub-Saharan Africa (i.e., locations south of the Tropic of Cancer); data on locations with a population of at least fifty thousand; data on locations from countries with a at least 750 conflict incidents over the study period; as well as some combinations of the foregoing subsets. This robustness check also validates the main results of this study.

Appendix Tables T3 and T4 replicate the main results while varying the cropland share thresholds that group grid cells into agricultural and non-agricultural categories. These results are consistent with those reported as the main results of the study.

As another check for parameter sensitivity, we re-estimate the main model by dropping (i) one year at a time, and (ii) one latitude at a time from the sample. Appendix Figures F3 and F4 present parameter estimates (for the harvest period and for the two subsequent periods of the marketing year) from these exercises, which largely corroborate the main results of this study.

Table 1: Main Results

	Conflict	Disaggregated by Actor:			
		State Forces	Rebel Groups	Political Militia	Identity Militia
Variables					
shock×harvest$_m$	0.119***	0.005	0.021	0.085**	0.006
	(0.037)	(0.009)	(0.011)	(0.028)	(0.006)
shock×harvest$_{m+1}$	0.192***	0.023	0.028*	0.133***	0.007
	(0.051)	(0.011)	(0.011)	(0.043)	(0.006)
shock×harvest$_{m+2}$	0.140***	0.018	0.034**	0.069**	0.019***
	(0.036)	(0.012)	(0.012)	(0.024)	(0.005)
shock×harvest$_{m+3}$	0.102**	0.011	0.020	0.062**	0.012
	(0.038)	(0.012)	(0.010)	(0.023)	(0.008)
shock×harvest$_{m+4}$	0.041	0.001	0.009	0.020	0.013
	(0.033)	(0.011)	(0.012)	(0.022)	(0.006)
shock×harvest$_{m+5}$	−0.009	−0.012	0.001	−0.012	0.015*
	(0.030)	(0.010)	(0.011)	(0.019)	(0.006)
shock×harvest$_{m+6}$	0.008	−0.006	0.033***	−0.019	0.001
	(0.031)	(0.011)	(0.010)	(0.018)	(0.011)
shock×harvest$_{m+7}$	0.028	−0.004	0.025**	−0.015	0.021***
	(0.028)	(0.010)	(0.009)	(0.018)	(0.006)
shock×harvest$_{m+8}$	0.031	0.013	0.018	−0.004	0.005
	(0.026)	(0.010)	(0.010)	(0.017)	(0.007)
shock×harvest$_{m+9}$	0.049	0.023	0.014	−0.003	0.014
	(0.027)	(0.011)	(0.010)	(0.018)	(0.006)
shock×harvest$_{m+10}$	0.096**	0.032	0.031**	0.019	0.014
	(0.031)	(0.016)	(0.010)	(0.019)	(0.007)
shock×harvest$_{m+11}$	0.070*	0.015	0.019	0.021	0.013
	(0.029)	(0.013)	(0.012)	(0.017)	(0.007)
Fixed effects					
grid cell	Y	Y	Y	Y	Y
year–month	Y	Y	Y	Y	Y
Number of Obs.	730,944	730,944	730,944	730,944	730,944

Note: the dependent variable is the number of conflict incidents per million population; shock is the annual growth of the price for the prevalent crop in a grid cell; harvest$_m$ is the harvest month, harvest$_{m+1}$ is the next month, and so forth until harvest$_{m+11}$, which is the last month of the marketing year (and, by default, a month before the harvest); observations are weighted by grid cell population, and standard errors (in parentheses) are clustered at the grid cell level; ***, **, and * denote 0.01, 0.05, and 0.10 significance levels based on Bonferroni–adjusted p-values.

We also perform several placebo checks. First, we re-estimate the parameters by applying one– and two–year lags and leads of the prices. Appendix Table T5 displays the results of this exercise, which show that parameter estimates are small and, by and large, statistically insignificant when leads and lags of the prices are applied. Second, following Crost and Felter (2020) for example, we re-estimate the parameters using sugar prices, instead of cereal prices, in the regressions. Appendix Table T6 presents these parameter estimates, which appear small and, for the most part, statistically insignificant. Finally, we run 100 simulations, in which we randomize the harvest seasons across locations. On average, we should find no seasonal pattern in this exercise. Appendix Figure F5 illustrates the point estimates and their confidence intervals from these 100 simulations, together with those from the main regression. The simulated data with randomized harvest seasons do not replicate the observed seasonal pattern of conflict.

6 Conclusion

Using monthly data on violence against civilians, as well as international prices of 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 this relationship, 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. 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 subsetting.

This finding corroborates the recent literature on the topic (Koren, 2018; McGuirk and Burke, 2020). We advance this literature by examining the role of seasonality in the income–conflict nexus. The results of this study offer more temporally nuanced evidence of the linkage between price shocks and conflict. This new finding matters, as it points to a likely temporal displacement of agricultural income–related conflict in the cropland of Africa. This can facilitate more effective planning by local or international communities toward mitigating conflict or avoiding ambush when operating in conflict–prone regions.

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Appendix Tables and Figures

This appendix presents tables and figures that are referred to in the main text of the manuscript.

Table T1: Results across varying fixed effects

Variables	Main	R1	R2	R3	R4
Variables					
shock×harvest$_m$	0.119***	0.082**	0.128***	0.089**	0.046
	(0.037)	(0.030)	(0.037)	(0.030)	(0.025)
shock×harvest$_{m+1}$	0.192***	0.150***	0.201***	0.158***	0.108**
	(0.051)	(0.044)	(0.051)	(0.045)	(0.037)
shock×harvest$_{m+2}$	0.140***	0.081***	0.155***	0.095***	0.040
	(0.036)	(0.025)	(0.036)	(0.026)	(0.021)
shock×harvest$_{m+3}$	0.102**	0.056	0.115**	0.066	0.022
	(0.038)	(0.030)	(0.038)	(0.031)	(0.029)
shock×harvest$_{m+4}$	0.041	0.011	0.053	0.021	−0.012
	(0.033)	(0.026)	(0.032)	(0.026)	(0.024)
shock×harvest$_{m+5}$	−0.009	−0.029	0.002	−0.020	−0.050
	(0.030)	(0.024)	(0.030)	(0.024)	(0.026)
shock×harvest$_{m+6}$	0.008	−0.008	0.017	−0.001	−0.020
	(0.031)	(0.026)	(0.031)	(0.026)	(0.024)
shock×harvest$_{m+7}$	0.028	0.015	0.034	0.019	−0.002
	(0.028)	(0.020)	(0.028)	(0.021)	(0.018)
shock×harvest$_{m+8}$	0.031	0.017	0.037	0.021	−0.018
	(0.026)	(0.021)	(0.026)	(0.021)	(0.019)
shock×harvest$_{m+9}$	0.049	0.020	0.056	0.026	−0.017
	(0.027)	(0.020)	(0.027)	(0.020)	(0.018)
shock×harvest$_{m+10}$	0.096**	0.074**	0.105***	0.081***	0.029
	(0.031)	(0.024)	(0.031)	(0.024)	(0.022)
shock×harvest$_{m+11}$	0.070*	0.041	0.080**	0.049*	−0.002
	(0.029)	(0.021)	(0.029)	(0.021)	(0.020)
Fixed effects					
grid cell	Y	Y	Y	Y	Y
year–month	Y		Y		
year		Y		Y	
country–year					Y
country–trend			Y	Y	
Number of Obs.	730,944	730,944	730,944	730,944	730,944

Note: the dependent variable is the number of conflict incidents per million population; shock is the annual growth of the price for the prevalent crop in a grid cell; harvest$_m$ is the harvest month, harvest$_{m+1}$ is the next month, and so forth until harvest$_{m+11}$, which is the last month of the marketing year (and, by default, a month before harvest); observations are weighted by grid cell population, and standard errors (in parentheses) are clustered at the grid cell level; ***, **, and * denote 0.01, 0.05, and 0.10 significance levels based on Bonferroni–adjusted p-values.

Table T2: Results across different data subsets

	Sub-Saharan	Populous	Conflict-prone (grid cells)	Conflict-prone (incidents)	Mid-Size countries
Variables					
shock×harvest$_{m}$	0.155***	0.110**	0.118**	0.206***	0.120**
	(0.043)	(0.037)	(0.040)	(0.058)	(0.043)
shock×harvest$_{m+1}$	0.232***	0.184***	0.190***	0.287***	0.200***
	(0.062)	(0.051)	(0.056)	(0.077)	(0.059)
shock×harvest$_{m+2}$	0.175***	0.132***	0.140***	0.241***	0.128***
	(0.043)	(0.036)	(0.038)	(0.052)	(0.040)
shock×harvest$_{m+3}$	0.146***	0.095*	0.089	0.191***	0.084
	(0.047)	(0.038)	(0.039)	(0.058)	(0.042)
shock×harvest$_{m+4}$	0.083	0.038	0.056	0.112	0.039
	(0.039)	(0.033)	(0.035)	(0.049)	(0.038)
shock×harvest$_{m+5}$	0.016	−0.014	−0.016	0.049	−0.033
	(0.038)	(0.030)	(0.032)	(0.040)	(0.033)
shock×harvest$_{m+6}$	0.024	0.003	−0.009	0.049	−0.013
	(0.037)	(0.031)	(0.032)	(0.044)	(0.034)
shock×harvest$_{m+7}$	0.028	0.021	0.019	0.060	0.016
	(0.034)	(0.028)	(0.029)	(0.037)	(0.030)
shock×harvest$_{m+8}$	0.036	0.024	0.014	0.069	0.042
	(0.032)	(0.026)	(0.026)	(0.037)	(0.028)
shock×harvest$_{m+9}$	0.052	0.044	0.034	0.113**	0.050
	(0.032)	(0.027)	(0.028)	(0.040)	(0.030)
shock×harvest$_{m+10}$	0.108**	0.087**	0.079*	0.168***	0.084*
	(0.037)	(0.031)	(0.031)	(0.046)	(0.035)
shock×harvest$_{m+11}$	0.085**	0.065	0.066	0.122**	0.071
	(0.033)	(0.029)	(0.030)	(0.044)	(0.032)
Fixed effects					
grid cell	Y	Y	Y	Y	Y
year–month	Y	Y	Y	Y	Y
Number of Obs.	609,120	443,304	698,688	402,048	705,600

Note: the dependent variable is the number of conflict incidents per million population; shock is the annual growth of the price for the prevalent crop in a grid cell; harvest$_{m}$ is the harvest month, harvest$_{m+1}$ is the next month, and so forth until harvest$_{m+11}$, which is the last month of the marketing year; observations are weighted by grid cell population, and standard errors (in parentheses) are clustered at the grid cell level; ***, **, and * denote 0.01, 0.05, and 0.10 significance levels based on Bonferroni–adjusted p-values. 'Sub-Saharan' denotes the data subset on locations south of the Tropic of Cancer; 'Populous' denotes the data subset on locations with population of at least 50 thousand (on average over the study period); 'Conflict-prone (grid cells)' denotes data subset on locations from countries with at least 10 grid cells with conflict incidents over the study period; 'Conflict-prone (incidents)' denotes data subset on locations from countries with at least 750 conflict incidents over the study period; 'Mid-size countries' denotes data subset on locations from countries with population of at least one million and at most 100 million (on average over the study period).

Table T3: Results using a lower threshold (0.005) of the cropland share

	Conflict	Disaggregated by Actor:			
		State Forces	Rebel Groups	Political Militia	Identity Militia
Variables					
shock×harvest$_m$	0.131***	0.010	0.023	0.087***	0.009
	(0.036)	(0.010)	(0.012)	(0.027)	(0.007)
shock×harvest$_{m+1}$	0.203***	0.029**	0.028	0.135***	0.011
	(0.048)	(0.011)	(0.012)	(0.039)	(0.006)
shock×harvest$_{m+2}$	0.150***	0.022	0.032*	0.073***	0.021***
	(0.034)	(0.012)	(0.013)	(0.022)	(0.006)
shock×harvest$_{m+3}$	0.108***	0.012	0.018	0.063**	0.017
	(0.037)	(0.012)	(0.011)	(0.022)	(0.008)
shock×harvest$_{m+4}$	0.058	0.006	0.009	0.025	0.022*
	(0.033)	(0.011)	(0.012)	(0.020)	(0.009)
shock×harvest$_{m+5}$	0.003	−0.008	0.001	−0.006	0.017*
	(0.028)	(0.010)	(0.011)	(0.017)	(0.007)
shock×harvest$_{m+6}$	0.010	−0.005	0.033**	−0.024	0.007
	(0.030)	(0.010)	(0.011)	(0.019)	(0.011)
shock×harvest$_{m+7}$	0.060	0.001	0.029**	0.006	0.024***
	(0.032)	(0.010)	(0.010)	(0.022)	(0.007)
shock×harvest$_{m+8}$	0.048	0.019	0.019	0.002	0.009
	(0.026)	(0.010)	(0.010)	(0.016)	(0.008)
shock×harvest$_{m+9}$	0.062	0.029**	0.016	−0.001	0.016*
	(0.027)	(0.011)	(0.011)	(0.018)	(0.007)
shock×harvest$_{m+10}$	0.107***	0.033	0.030**	0.028	0.016
	(0.030)	(0.014)	(0.011)	(0.018)	(0.007)
shock×harvest$_{m+11}$	0.078**	0.015	0.018	0.028	0.015
	(0.029)	(0.012)	(0.013)	(0.017)	(0.007)
Fixed effects					
grid cell	Y	Y	Y	Y	Y
year–month	Y	Y	Y	Y	Y
Number of Obs.	730,944	730,944	730,944	730,944	730,944

Note: the dependent variable is the number of conflict incidents per million population; shock is the annual growth of the price for the prevalent crop in a grid cell; harvest$_m$ is the harvest month, harvest$_{m+1}$ is the next month, and so forth until harvest$_{m+11}$, which is the last month of the marketing year (and, by default, a month before the harvest); observations are weighted by grid cell population, and standard errors (in parentheses) are clustered at the grid cell level; ***, **, and * denote 0.01, 0.05, and 0.10 significance levels based on Bonferroni–adjusted p-values.

Table T4: Results using a higher threshold (0.02) of the cropland share

	Conflict	Disaggregated by Actor:			
		State Forces	Rebel Groups	Political Militia	Identity Militia
Variables					
shock×harvest$_m$	0.132**	0.001	0.011	0.115***	0.007
	(0.044)	(0.009)	(0.010)	(0.037)	(0.006)
shock×harvest$_{m+1}$	0.214***	0.019	0.019	0.166**	0.007
	(0.062)	(0.011)	(0.011)	(0.054)	(0.006)
shock×harvest$_{m+2}$	0.156***	0.022	0.024	0.091***	0.019***
	(0.039)	(0.011)	(0.012)	(0.028)	(0.006)
shock×harvest$_{m+3}$	0.135***	0.015	0.015	0.091***	0.015
	(0.039)	(0.012)	(0.010)	(0.026)	(0.008)
shock×harvest$_{m+4}$	0.054	0.006	0.002	0.036	0.013
	(0.034)	(0.010)	(0.012)	(0.024)	(0.007)
shock×harvest$_{m+5}$	0.015	−0.015	−0.002	0.017	0.017*
	(0.029)	(0.009)	(0.013)	(0.018)	(0.007)
shock×harvest$_{m+6}$	0.040	−0.001	0.019	0.013	0.009
	(0.028)	(0.011)	(0.009)	(0.016)	(0.010)
shock×harvest$_{m+7}$	0.038	0.001	0.013	0.001	0.023***
	(0.026)	(0.008)	(0.008)	(0.017)	(0.007)
shock×harvest$_{m+8}$	0.046	0.008	0.013	0.018	0.007
	(0.024)	(0.007)	(0.010)	(0.016)	(0.008)
shock×harvest$_{m+9}$	0.061*	0.020	0.009	0.024	0.009
	(0.026)	(0.011)	(0.009)	(0.018)	(0.006)
shock×harvest$_{m+10}$	0.115***	0.034	0.027**	0.038	0.017**
	(0.032)	(0.018)	(0.010)	(0.017)	(0.006)
shock×harvest$_{m+11}$	0.073*	0.011	0.013	0.041*	0.008
	(0.029)	(0.013)	(0.012)	(0.017)	(0.006)
Fixed effects					
grid cell	Y	Y	Y	Y	Y
year–month	Y	Y	Y	Y	Y
Number of Obs.	730,944	730,944	730,944	730,944	730,944

Note: the dependent variable is the number of conflict incidents per million population; shock is the annual growth of the price for the prevalent crop in a grid cell; harvest$_m$ is the harvest month, harvest$_{m+1}$ is the next month, and so forth until harvest$_{m+11}$, which is the last month of the marketing year (and, by default, a month before the harvest); observations are weighted by grid cell population, and standard errors (in parentheses) are clustered at the grid cell level; ***, **, and * denote 0.01, 0.05, and 0.10 significance levels based on Bonferroni–adjusted p-values.

Table T5: Results using lags and leads of the prices

	2–year lag	1–year lag	Main results	1–year lead	2–year lead
Variables					
shock×harvest$_m$	0.005	0.057	0.119***	0.004	−0.003
	(0.035)	(0.037)	(0.037)	(0.032)	(0.033)
shock×harvest$_{m+1}$	0.001	0.081	0.192***	−0.034	−0.031
	(0.026)	(0.040)	(0.051)	(0.045)	(0.032)
shock×harvest$_{m+2}$	−0.028	0.032	0.140***	0.015	−0.053
	(0.025)	(0.023)	(0.036)	(0.029)	(0.040)
shock×harvest$_{m+3}$	0.006	0.039	0.102**	−0.011	−0.035
	(0.030)	(0.030)	(0.038)	(0.031)	(0.036)
shock×harvest$_{m+4}$	−0.023	−0.005	0.041	−0.027	−0.074
	(0.028)	(0.029)	(0.033)	(0.032)	(0.038)
shock×harvest$_{m+5}$	0.001	−0.040	−0.009	−0.029	−0.069
	(0.029)	(0.030)	(0.030)	(0.030)	(0.041)
shock×harvest$_{m+6}$	−0.045	0.022	0.008	0.030	−0.069
	(0.031)	(0.026)	(0.031)	(0.028)	(0.035)
shock×harvest$_{m+7}$	−0.031	0.019	0.028	0.062**	−0.025
	(0.036)	(0.024)	(0.028)	(0.024)	(0.035)
shock×harvest$_{m+8}$	−0.040	0.023	0.031	0.044	−0.025
	(0.032)	(0.022)	(0.026)	(0.026)	(0.030)
shock×harvest$_{m+9}$	−0.061	0.034	0.049	0.069**	0.026
	(0.035)	(0.024)	(0.027)	(0.026)	(0.032)
shock×harvest$_{m+10}$	−0.051	0.043	0.096**	0.076	0.058
	(0.043)	(0.028)	(0.031)	(0.045)	(0.041)
shock×harvest$_{m+11}$	−0.028	0.041	0.070*	0.050	0.040
	(0.041)	(0.023)	(0.029)	(0.028)	(0.040)
Fixed effects					
grid cell	Y	Y	Y	Y	Y
year–month	Y	Y	Y	Y	Y
Number of Obs.	670,032	700,488	730,944	700,488	670,032

Note: the dependent variable is the number of conflict incidents per million population; shock is the annual growth of the international sugar price index obtained from the Food and Agriculture Organization of the United Nations, available at http://www.fao.org/worldfoodsituation/foodpricesindex/en/; harvest$_m$ is the harvest month, harvest$_{m+1}$ is the next month, and so forth until harvest$_{m+11}$, which is the last month of the marketing year (and, by default, a month before the harvest); observations are weighted by grid cell population, and standard errors (in parentheses) are clustered at the grid cell level; ***, **, and * denote 0.01, 0.05, and 0.10 significance levels based on Bonferroni–adjusted p-values.

Table T6: Results using sugar prices

	Conflict	Disaggregated by Actor:			
		State Forces	Rebel Groups	Political Militia	Identity Militia
Variables					
shock×harvest$_m$	0.048	0.008	−0.011	0.042	0.006
	(0.032)	(0.008)	(0.015)	(0.020)	(0.007)
shock×harvest$_{m+1}$	0.057	−0.003	−0.012	0.056	0.010
	(0.034)	(0.009)	(0.015)	(0.025)	(0.005)
shock×harvest$_{m+2}$	0.034	−0.002	−0.005	0.028	0.009
	(0.030)	(0.008)	(0.017)	(0.015)	(0.005)
shock×harvest$_{m+3}$	0.016	−0.005	−0.012	0.018	0.011
	(0.031)	(0.011)	(0.016)	(0.015)	(0.007)
shock×harvest$_{m+4}$	0.009	0.001	−0.027	0.024	0.007
	(0.029)	(0.008)	(0.017)	(0.015)	(0.008)
shock×harvest$_{m+5}$	0.008	0.014	−0.024	0.008	0.007
	(0.031)	(0.010)	(0.017)	(0.017)	(0.006)
shock×harvest$_{m+6}$	0.009	0.015	−0.019	0.008	0.003
	(0.029)	(0.009)	(0.015)	(0.017)	(0.007)
shock×harvest$_{m+7}$	−0.001	0.005	−0.016	0.007	−0.004
	(0.032)	(0.008)	(0.016)	(0.018)	(0.007)
shock×harvest$_{m+8}$	−0.014	−0.002	−0.007	−0.011	0.001
	(0.032)	(0.009)	(0.015)	(0.019)	(0.006)
shock×harvest$_{m+9}$	0.035	0.007	−0.010	0.013	0.020
	(0.032)	(0.009)	(0.016)	(0.016)	(0.013)
shock×harvest$_{m+10}$	0.025	−0.001	−0.005	−0.003	0.031**
	(0.030)	(0.009)	(0.016)	(0.016)	(0.011)
shock×harvest$_{m+11}$	0.054	0.005	−0.011	0.033*	0.024
	(0.029)	(0.009)	(0.016)	(0.014)	(0.011)
Fixed effects					
grid cell	Y	Y	Y	Y	Y
year–month	Y	Y	Y	Y	Y
Number of Obs.	730,944	730,944	730,944	730,944	730,944
Adjusted R^2	0.12	0.05	0.05	0.10	0.06

Note: the dependent variable is the number of conflict incidents per million population; shock is the annual growth of the international sugar price index obtained from the Food and Agriculture Organization of the United Nations, available at http://www.fao.org/worldfoodsituation/foodpricesindex/en/; harvest$_m$ is the harvest month, harvest$_{m+1}$ is the next month, and so forth until harvest$_{m+11}$, which is the last month of the marketing year (and, by default, a month before the harvest); observations are weighted by grid cell population, and standard errors (in parentheses) are clustered at the grid cell level; ***, **, and * denote 0.01, 0.05, and 0.10 significance levels based on Bonferroni–adjusted p-values.

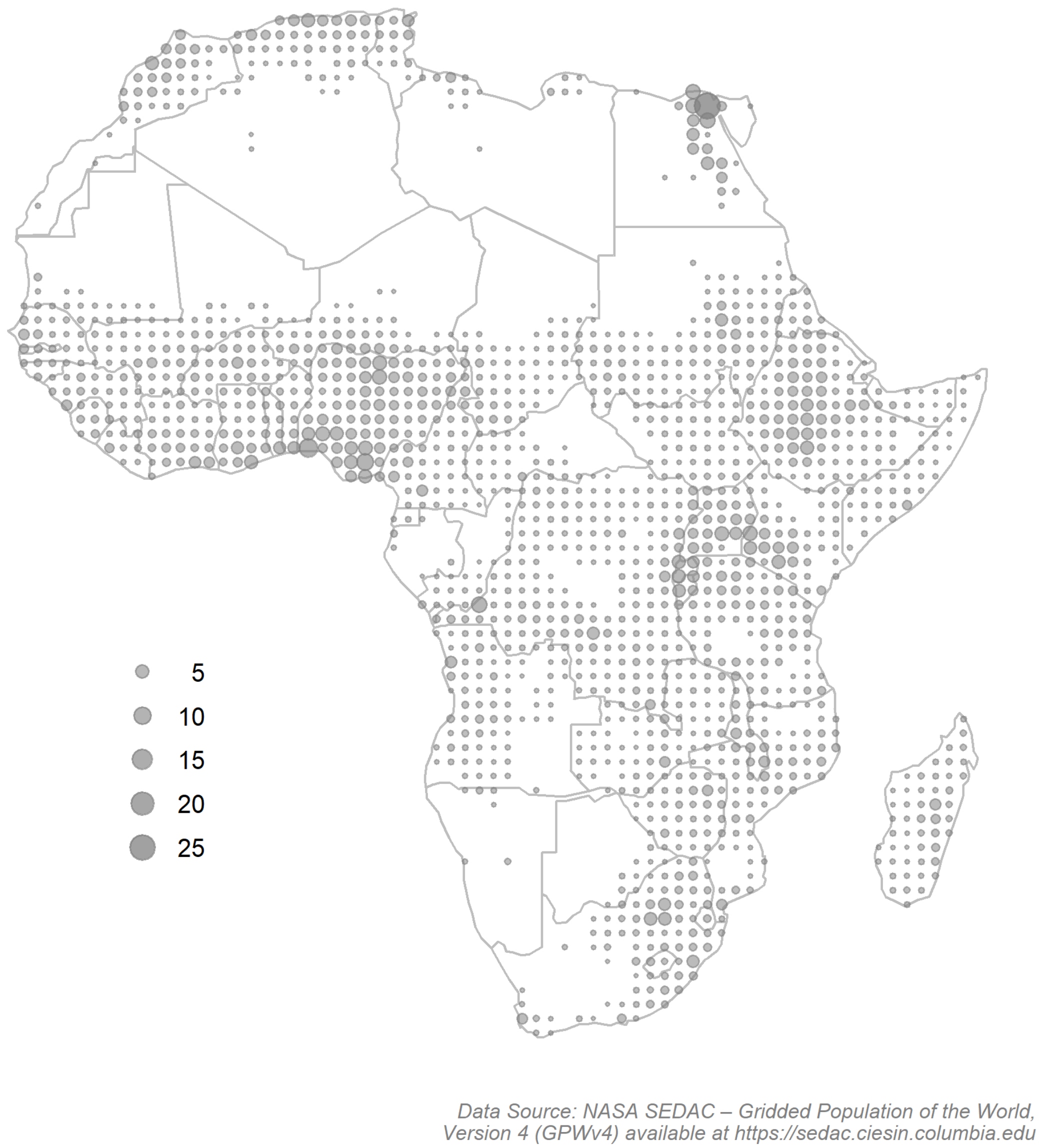

Figure F1: Geographic density of population across Africa
Note: Grid cells with average population of at least 50 thousand over 1997-2020 period are presented. The values are in millions.

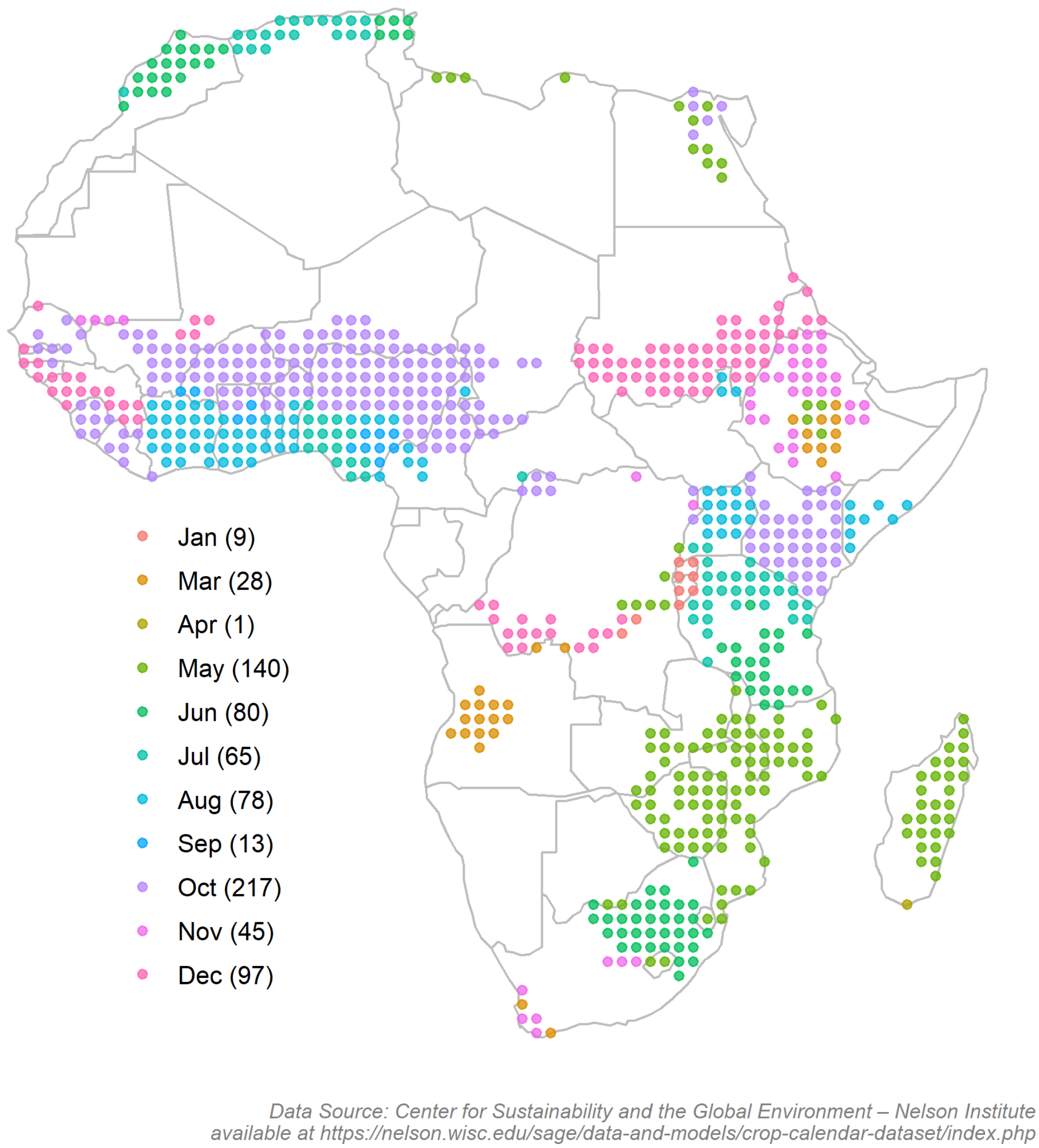

Figure F2: Geographic distribution of major crops' harvest months

Note: Grid cells with at least 0.01 share of cropland are presented. The values in parentheses, next to the month, indicate the number of grid cells that harvest in that month.

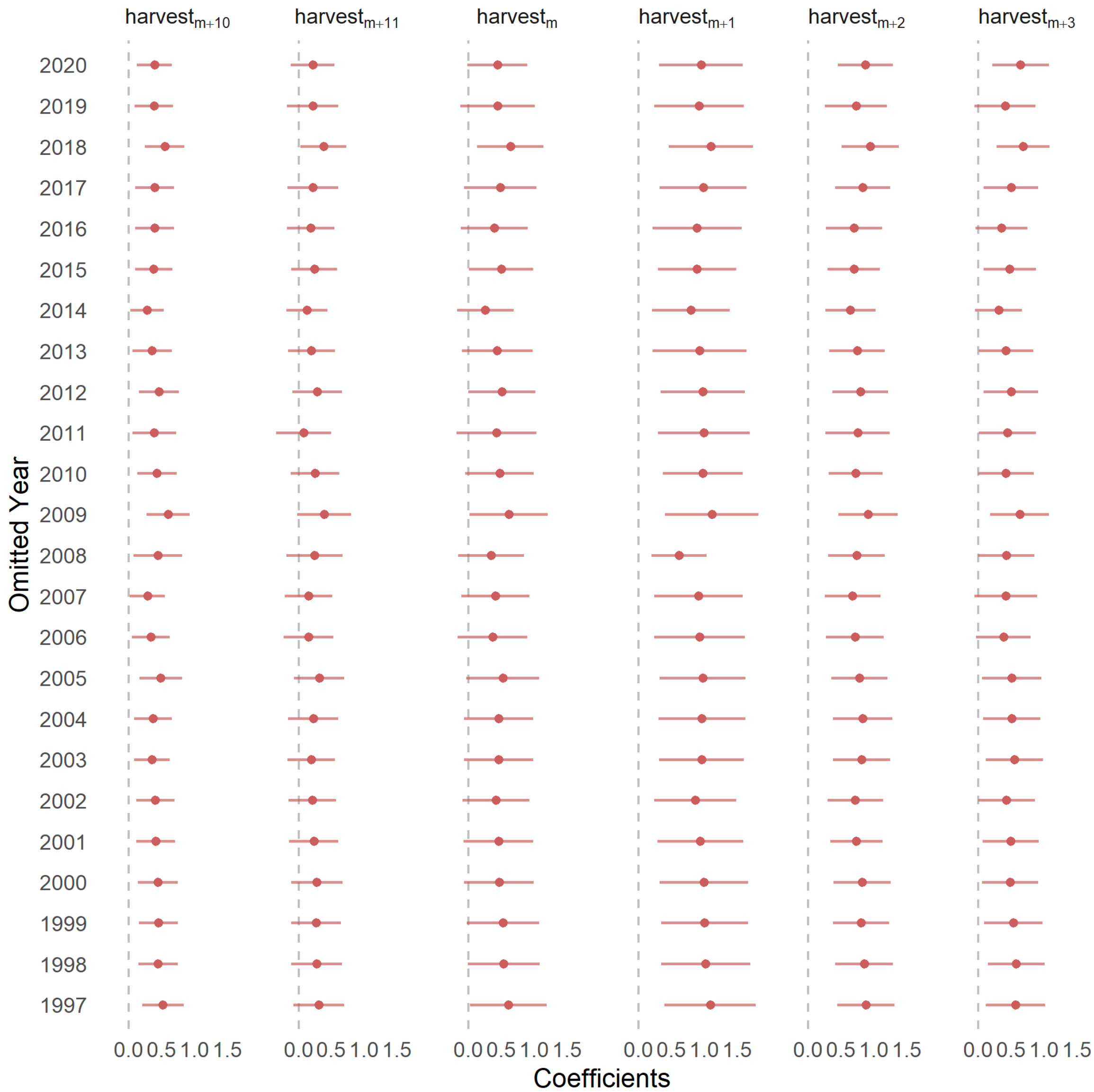

Figure F3: Parameter sensitivity to omitted years

Note: Dots are parameter estimates, and error-bars are 95 percent confidence intervals. In the interest of space, presented are parameters for the two months leading the harvest period, the harvest month, and the subsequent three months only.

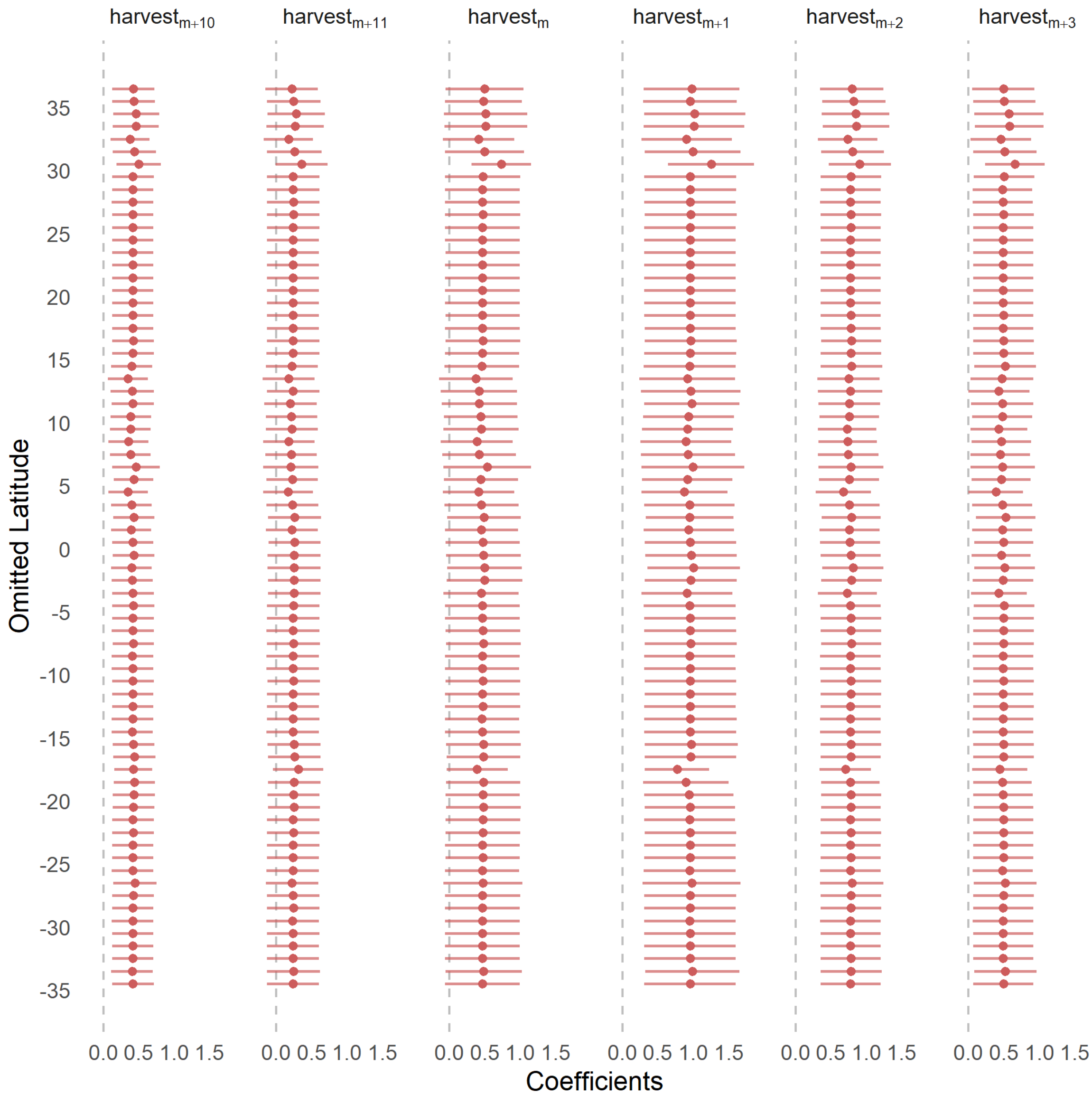

Figure F4: Parameter sensitivity to omitted latitudes

Note: Dots are parameter estimates, and error-bars are 95 percent confidence intervals. In the interest of space, presented are parameters for the two months leading the harvest period, the harvest month, and the subsequent three months only.

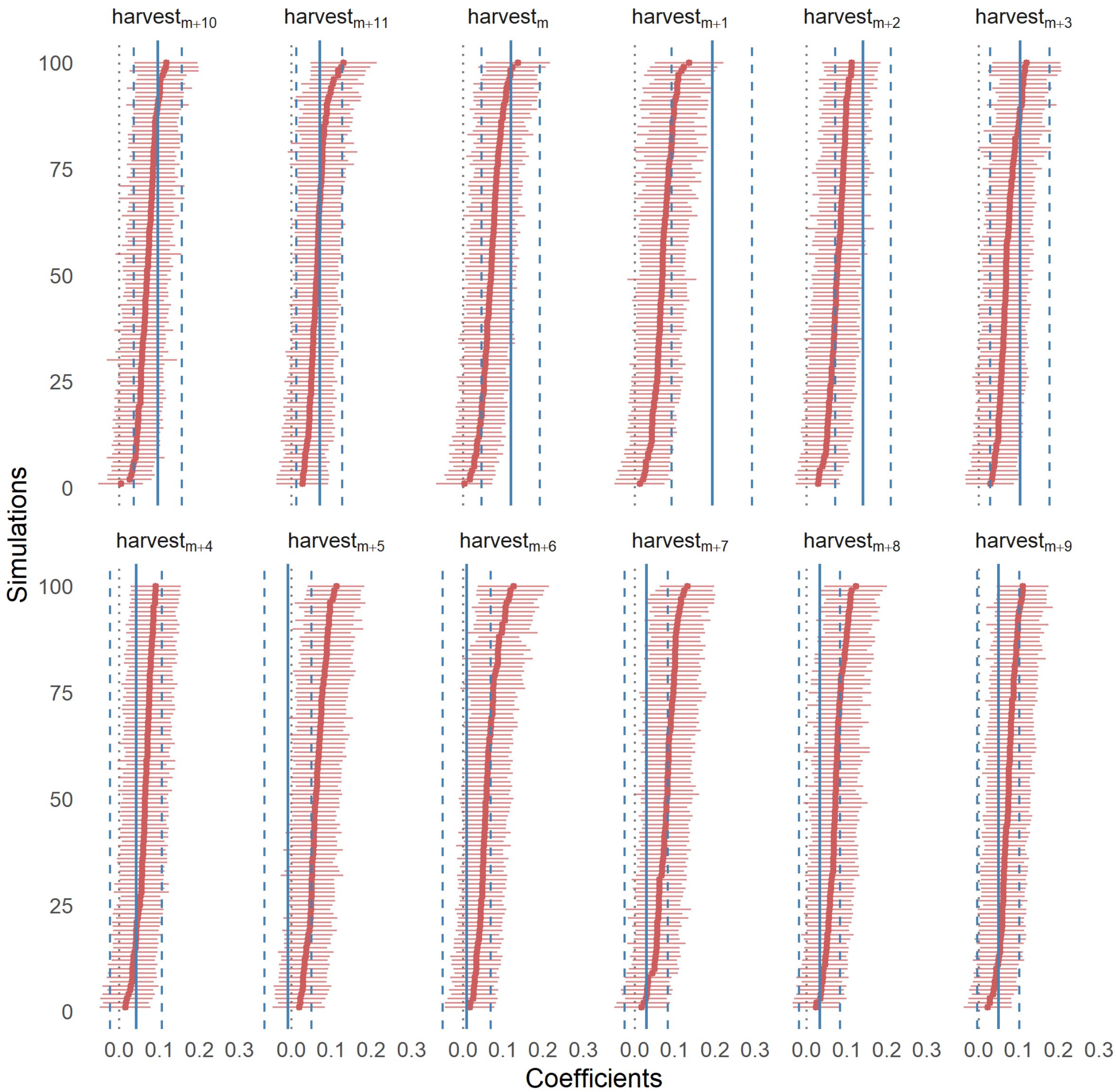

Figure F5: Parameter estimates from randomly assigned harvest seasons

Note: Red dots are parameter estimates, and error-bars are 95 percent confidence intervals from regressions with randomly assigned harvest seasons. Blue solid lines are parameter estimates, and dashed lines are 95 percent confidence intervals from the main regression.