Prices and Protests: Evidence from Maize Markets Across Africa*

Aaron Humphreys — HoustonKemp

David Ubilava† — University of Sydney

October 27, 2025

Abstract

We provide new evidence on how changes in local maize prices affect social unrest across 87 markets in 18 African countries. Contrary to a widely held perception, we find that an increase in the price of this key commodity—which benefits producers but harms consumers—reduces social unrest. This average effect masks important heterogeneity: in areas more suitable for maize cultivation, rising prices lower the likelihood of riots, whereas they increase it in areas with greater inequality in maize production across ethnic lines. We corroborate the proposed mechanism—that the effect is driven by differential income impacts across groups—using individual-level data from Afrobarometer surveys. We show that higher maize prices improve the well-being of agricultural workers but reduce that of non-agricultural workers. Our findings highlight the importance of the distributional effects of income shocks and their implications for conflict.

Keywords: Commodity markets, income shocks, prices, social unrest.
JEL Codes: D74, O13, Q11.

*This paper evolved from Aaron Humphreys' honours thesis, completed while he was a student at the University of Sydney. From that version to the current one, there have been substantial changes in both research execution and results. David Ubilava acknowledges financial support from the Australian Research Council under its Discovery Projects funding scheme (DP240101563). Antonn Park provided valuable editorial assistance that improved the clarity and readability of the paper.

†Corresponding author: david.ubilava@sydney.edu.au

1 Introduction

Income shocks are an important correlate of conflict (e.g., Miguel et al., 2004; Ray and Esteban, 2017), which remains a major barrier to growth and development (Rodrik, 1999; Collier and Hoeffler, 2002; Gates et al., 2012). In low- and middle-income countries, where most households spend a substantial share of their income on food, an increase in food prices typically manifests as a negative income shock. However, this effect is far from universal. A non-trivial share of households in these countries also earn much of their income by selling the food they produce. Thus, while higher food prices tend to hurt net consumers, they benefit net producers, i.e., those engaged in the agricultural sector. Understanding the distributional effects of food price shocks is particularly important in settings with high agricultural reliance and institutional fragility, where (relative) income shifts can trigger conflict.

In this paper, we examine how changes in local prices cause conflict—social unrest in particular—in Sub-Saharan Africa. Any attempt to empirically investigate the relationship between local food prices and conflict inevitably faces identification challenges, not least because of reverse causality, as conflict can affect local supply and in turn local prices. For example, conflict may draw agricultural workers away from farms or even lead to the destruction of farmland (Koren, 2019) as well as disrupt the functioning of food markets (Hastings et al., 2022). To circumvent this endogeneity issue, studies have used global prices, typically in a reduced-form setting, on the grounds that they are exogenous to local conflicts (Brückner and Ciccone, 2010; Berman and Couttenier, 2015; McGuirk and Burke, 2020; Crost et al., 2025). By adopting this approach, they test the effect of global prices on local conflict while assuming that global and local markets are integrated and thus shocks to global prices are transmitted to local prices.

We make the same assumption that global and local maize markets are integrated but further assume that global prices affect local conflict only through their impact on local prices. In other words, local prices are not just an important link but also the only link through which global prices can propagate conflict. Given the relatively high frequency of the data used in our study, we argue that any other channel through which global prices might influence local conflict is unlikely to confound our estimates. Such alternative channels—for example, if either the state or the opposition/insurgents were to gain windfalls from rising international prices (an unlikely outcome given the region's limited maize export potential), or if a sudden global price spike were to strain cash flows or subsidy budgets in maize-importing countries, thereby affecting state capacity or security spending before local retail prices fully adjust—are unlikely to operate independently of the local price and, in any case, they would plausibly operate only at lower temporal frequencies and with greater delay.

We estimate the effect of food prices on social unrest using monthly maize prices from 87 markets located across 18 countries in Sub-Saharan Africa, instrumented by international prices of the most commonly traded maize. We focus on this region not only because data on conflict and prices are relatively abundant compared to other regions but also because it is characterized by widespread poverty and a heavy reliance on agricultural employment. As a result, even relatively small changes in food prices can substantially affect household incomes and well-being, thereby heightening the risk of conflict. Furthermore, we focus on a specific form of conflict—social unrest, comprising protests and riots—because it tends to be more spontaneous and thus more susceptible to short-term price fluctuations.

In our baseline specification, we find negative association between prices and social unrest. Specifically, we find that a 10% increase in the maize price—a change equivalent to an average monthly price change observed across markets—reduces the probability of social unrest by 6.7% relative to the unconditional mean of the incidence of social unrest, which we use as the benchmark. The effects are smaller and statistically indistinguishable from zero for the specific forms of social unrest, i.e., protests and riots.

In our main specification, which accounts for the suitability of cropland for maize production and for maize production inequality across ethnic boundaries comprising the geographic unit of observation, we find that in locations with no maize agriculture, a 10% increase in the maize price reduces social unrest, primarily protests rather than riots, by 7.5% relative to baseline. This effect is more pronounced in locations with maize agriculture and muted (and perhaps even reversed) in locations with substantial differences in maize production across ethnic boundaries within the geographic unit of observation. These differential effects are somewhat noisy for protests, or social unrest in general, but are estimated more precisely for riots. Specifically, a differential effect of the same price change corresponds to a 5.5% decrease in locations with the average observed maize cropland (relative to those with no maize cropland) and a 6.6% increase in locations with the average observed degree of maize production inequality (relative to ethnically homogeneous locations). These main results withstand robustness checks and are corroborated by mechanisms tests, including an empirical investigation of individual perceptions of well-being and socio-political tensions based on survey data from Afrobarometer.

We contribute to several interrelated strands of literature. First, we contribute to the literature studying the economic origins of conflict, specifically that of price-induced changes in income (Dube and Vargas, 2013; Mitra and Ray, 2014; Smith, 2014; Bellemare, 2015; Berman and Couttenier, 2015; Hendrix and Haggard, 2015; Crost and Felter, 2020; Berman et al., 2021; Panza and Swee, 2023; Ubilava et al., 2023; Davis et al., 2025). We estimate the (second-stage) effect of local price changes on conflict—a relationship that has been largely neglected, or bypassed, by previous income–conflict studies, which typically focus on the reduced-form effect of global price changes on local conflict. Moreover, by working with more temporally and spatially granular observations—monthly data observed at specific locations—and a more narrowly defined form of conflict—social unrest manifested through protests and riots—we can explore a more nuanced relationship between short-run price changes and conflict in Africa. This contrasts with most existing studies that rely on annual or quarterly data, focus on broader measures of more violent conflict events (e.g., civil wars or violence against civilians), and typically analyze spatially aggregated data—often at the country level—or global rather than local prices (Bazzi and Blattman, 2014; McGuirk and Burke, 2020; De Winne and Peersman, 2021; Davis et al., 2025).

Second, we contribute to the literature on the agro-climatic causes of conflict by focusing on prices across markets located in areas both highly and less suitable for maize production (Hendrix and Salehyan, 2012; Couttenier and Soubeyran, 2014; Harari and Ferrara, 2018; Mach et al., 2019; Ubilava, 2024; McGuirk and Nunn, 2025). By focusing on within-year periods of agricultural employment and food abundance linked to harvests, as well as between-year differences in harvest quality inferred from growing-season rainfall, we provide suggestive evidence on the mechanisms underlying the estimated effect. Our finding that the effect on protests is weak—if not absent—immediately after the harvest season, whereas the effect on riots is muted in years following relatively poor harvests, suggests that these differences across the two forms of social unrest stem from competing mechanisms—opportunity cost, resentment, and rapacity—that manifest in some contexts but not in others.

Third, we contribute to the literature on the ethnic roots of conflict (Esteban and Ray, 1994; Fearon and Laitin, 2003; Montalvo and Reynal-Querol, 2005; Østby, 2008; Ray and Esteban, 2017; Bazzi and Gudgeon, 2021; Manotas-Hidalgo et al., 2021; Berman et al., 2023; Bertinelli et al., 2025). Rather than focusing on the effect of ethnic fragmentation on conflict, we examine fragmentation as a source of income inequality in the wake of price shocks that may disproportionately affect some groups relative to others. Specifically, we explore this mechanism through disparities in agricultural dependence across ethnic boundaries within relatively confined geographic areas, thereby offering novel insights into the distributional effects of price shocks. We test this mechanism using data on historical ethnic homelands (Murdock, 1959, 1967) and further corroborate the relationship using individual-level survey data on ethnic background and occupation from multiple rounds of the Afrobarometer.

The remainder of the paper is structured as follows. Section 2 outlines the key mechanisms likely driving the results. Section 3 describes the data and variables used in the analysis. Section 4 introduces the empirical model and discusses its identifying assumptions. Section 5 presents the main findings, followed by robustness checks and mechanisms tests, as well as additional details on the Afrobarometer data. Section 6 concludes.

2 Background and Competing Mechanisms

Fleeting price increases not only exacerbate human suffering "but also threaten to destabilize the political and social order" (Barrett, 2022). The 21st century alone provides several examples of rising food prices coinciding with periods of amplified social unrest (Bellemare, 2015). The first of these shocks occurred during 2005–2008, when the real prices of staple crops, including those of wheat and maize, nearly doubled (Headey and Fan, 2008). Several studies have linked this spike in food prices to an increase in social unrest, particularly in developing countries (Berazneva and Lee, 2013; Bellemare, 2015). The second of these shocks began in 2010, when real food prices rose to levels comparable to those in the previous episode (Ivanic et al., 2012). This shock has been identified as a key contributor to the Arab Spring that resulted in the collapse of several governments in the Middle East and North Africa (MENA) region during the early 2010s (Sternberg, 2012; Soffiantini, 2020). The turbulence was not unique to the MENA region. Surging food prices, for example, triggered the 2010 riots in Mozambique, leaving dozens dead and hundreds arrested (BBC News, 2010).

These high-price episodes have fueled academic interest in studying the relationship between food prices and social unrest, which is situated within a broader literature examining the impact of income on conflict. However, the expected effect that changes in household income can have on conflict is ambiguous in terms of both direction and magnitude. Several competing theories have been offered, each with its empirical support.

On one side of this argument, the literature posits that an increase in food prices raises the risk of conflict. The relevant theory of greed (Collier and Hoeffler, 2004) is linked to the so-called rapacity mechanism, which suggests that rising food prices increase the value of agricultural output or the means of producing it (Dube and Vargas, 2013; Bellemare, 2015; Koren, 2018; McGuirk and Burke, 2020; Abidoye and Calì, 2021; De Winne and Peersman, 2021; Ubilava et al., 2023). This can lead to more violence, as militias or civilians resort to more violent ways of appropriating food or its sources. In the context of our study, violent forms of riots may fall in such a category of conflict.

On the same side, the theory of relative deprivation (Gurr, 1970) holds that rising food prices reduce real incomes (e.g., among the urban poor), leaving people feeling deprived relative to their past or to wealthier groups in society. Such perceptions of deprivation can fuel anger and resentment, leading to social unrest—a mechanism that has been empirically substantiated (Bellemare, 2015; Hendrix and Haggard, 2015; De Winne and Peersman, 2021). On the other hand, plummeting prices, which harm farmers, can also be a major source of grievance among farmers. So, there is likely a rural–urban or agricultural–non-agricultural divide in the ways price changes manifest in relative deprivation and conflict.

The theory also connects directly to the ethnic roots of unrest (Cederman et al., 2011). For example, Siroky et al. (2020) link perceived relative deprivation to the onset of ethnic conflict, while Guimond and Dambrun (2002) provide psychological evidence that inequality and perceived injustice heighten support for radical and confrontational behavior. A general consensus in the literature is that pre-existing ethnic-based differences create a channel through which intergroup resentment may emerge (Esteban and Ray, 2008; Østby, 2008).

On the other side of this argument, the literature suggests that rising food prices can reduce the risk of conflict and social unrest (Brückner and Ciccone, 2010). The relevant mechanism here is rooted in opportunity cost. Higher food prices increase potential wages and profits in the agricultural sector, raising the cost of time and resources spent on protesting. In the context of our study, this implies that for farmers and agricultural workers, the incentive to engage in unrest is lower when the prices of the goods they produce are high.

Combining these insights, we expect two short-run responses to an increase in the price of a locally produced staple crop. First, protests and riots should be less frequent in regions without deep historical cleavages and where a large share of the population are net producers of the crop, as the opportunity cost dominates the rapacity and resentment mechanisms. Second, there will be protests and riots in regions that are highly heterogeneous in terms of employment and income related to that crop, as the rapacity and resentment mechanisms likely dominate the opportunity cost.

3 Data and Variable Construction

Our data come from several publicly available online platforms. In this section, we first introduce the sources and provide specific details, including any manipulations made in compiling the final dataset. We then summarize the summary of descriptive statistics of the key variables used in the analysis.

3.1 Markets and Prices

We obtain local market-level price data from the Famine Early Warning Systems Network (FEWS NET), the Global Information and Early Warning System (GIEWS) of the Food and Agriculture Organization (FAO), and the World Food Programme (WFP). Data on international maize price series come from the Commodity Data Portal of the International Monetary Fund (IMF).

The FEWS NET, GIEWS, and WFP databases store a large number of monthly price series observed at different stages of the supply chain—typically retail and wholesale—across a large set of African markets. We focus exclusively on maize because it is one of the most widely produced and consumed staple cereal crops across Africa. Additionally, Africa's share of maize production on the international market is very small, meaning local shocks to maize production or prices cannot influence global maize prices.

While some series start as early as the late 1990s, many are either too short (spanning only a few years) or incomplete (with numerous missing observations). To retain the set of price series used in our analysis, we first retain locally procured retail price data for maize, ensuring prices were available (or could be converted) to U.S. dollars per kilogram. Second, we exclude price series that spanned less than 10 years and had more than 10% missing observations in total, or contained missing observations over four consecutive months. We opt for a relatively short span of the series to ensure large geographic coverage of markets, but the selected series are long enough to allow us to observe substantial within-market variation. A substantial share of the selected series overlap with historically relevant global market disruptions in the early 2010s and early 2020s (Ferguson and Ubilava, 2022).

Third, we remove price series that represent markets with overlapping catchment zones. We define a market catchment zone as an area within a 50-km radius of the market centroid, and sequentially eliminate markets with the smallest population count—using population data (within a 10-km radius of the market centroid) from WorldPop (2018)—until no overlaps remain. Such a market catchment zone is small enough to assume common prices and comparable motives for conflict yet large enough to capture location-specific characteristics (such as ethnic fragmentation, which we discuss below). This definition also places markets at least 100 km apart, which is a reasonable distance for treating them as separate markets.

We thus retain price series from 87 markets across 18 countries. Figure 1 illustrates the geographic coverage of these markets. The catchment zones vary from virtually no local maize production, for example, in the Sahel, to those with substantial maize production, for example, in parts of Nigeria, Kenya, and Malawi (see also Appendix Figure B1).

For global prices, we use U.S. No. 2 Yellow Maize (FOB Gulf of Mexico), obtained from the IMF. These global prices are plotted alongside the boxplots and averages of local prices presented in Figure 2. While in most periods most local prices are well above global prices, there is considerable co-movement between both, especially during episodes of rapid growth (e.g., 2008–2009, 2010–2011).

3.2 Protests and Riots

We obtain conflict data from the Armed Conflict Location & Event Data (ACLED) Project (Raleigh et al., 2010, 2023). ACLED provides granular data on conflict incidents categorized into six types: battles (between organized armed groups), explosions/remote violence (often, though not exclusively, carried out by organized armed groups), violence against civilians (perpetrated by organized armed groups), protests (relatively peaceful demonstrations), riots (more violent forms of public disorder), and strategic developments. These conflict types are

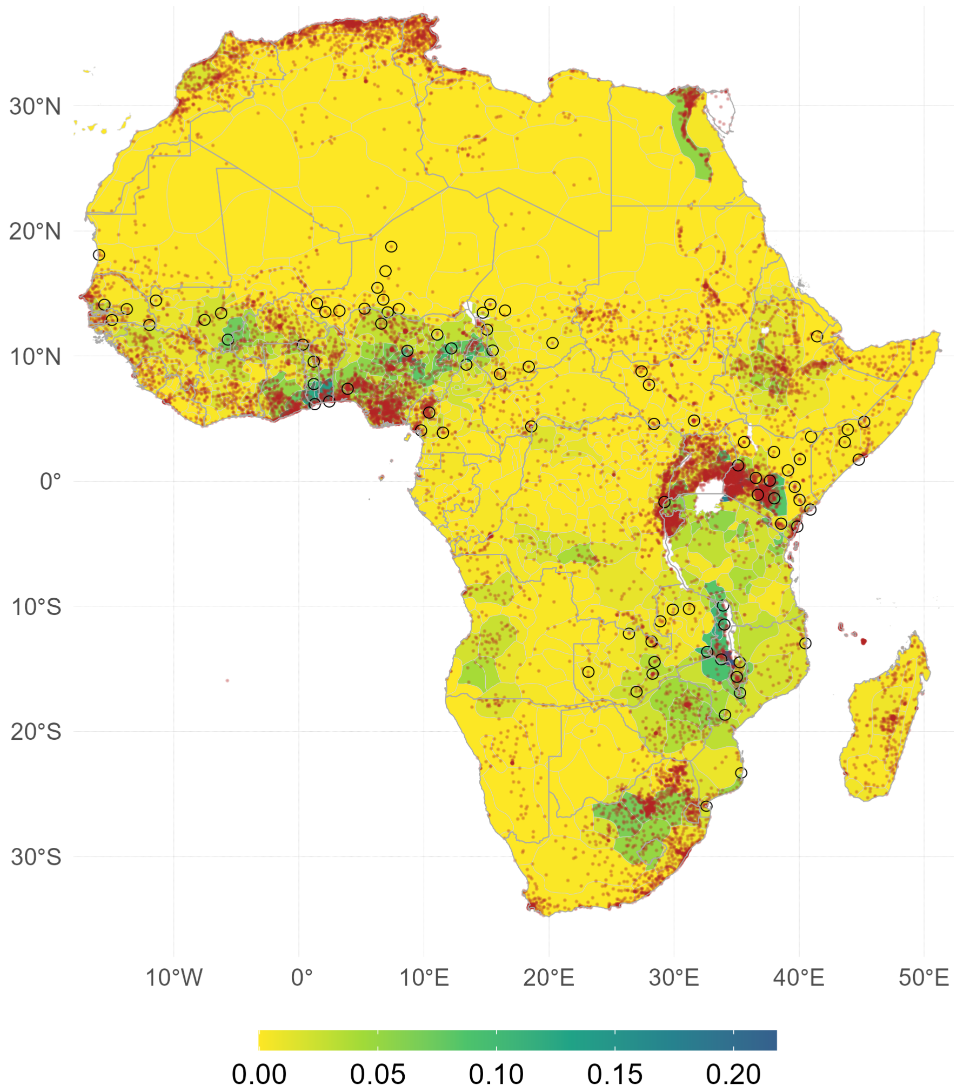

Figure 1: Maize Production, Ethnic Boundaries, and Social Unrest

Note: Polygons filled with a yellow–green gradient indicate the share of land under maize cultivation within ethnic boundaries, based on data from IFPRI (2019) and the Murdock map (Murdock, 1959, 1967). Empty circles denote market catchment zones derived from price data from FEWS NET, GIEWS, and the WFP. Red dots indicate protests or riots, as recorded in ACLED (Raleigh et al., 2023).

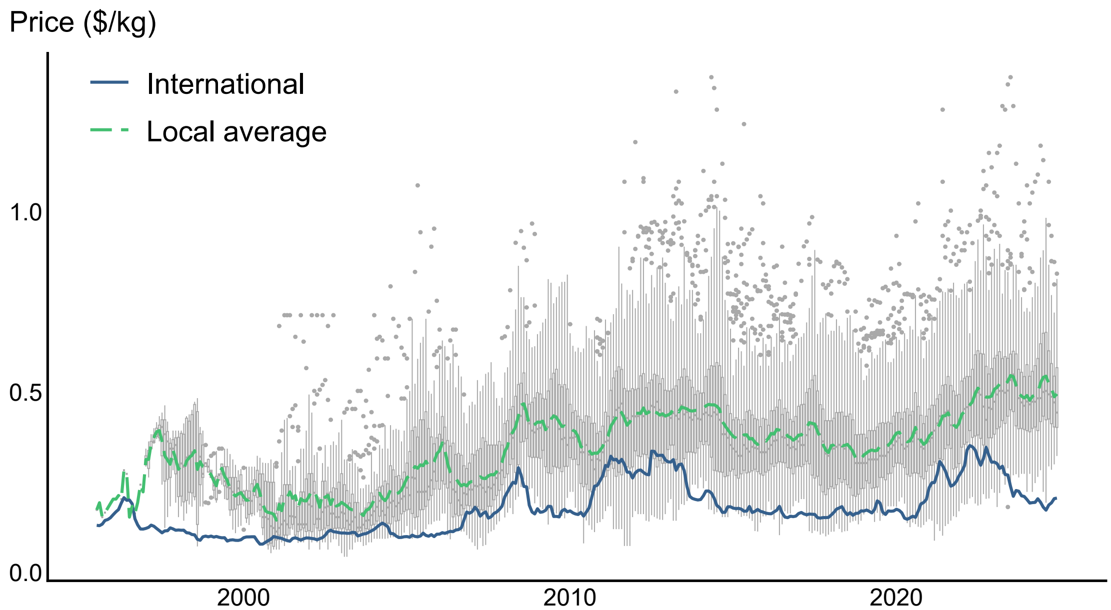

Figure 2: Local and International Maize Prices

Note: International prices are for U.S. No. 2 Yellow Maize, FOB Gulf of Mexico sourced from the Commodity Data Portal of the IMF. Local prices are (typically) for white maize sourced from FEWS NET, GIEWS, and the WFP.

further arranged into three broader disorder categories: political violence with or without civilian targeting (including battles, explosions/remote violence, violence against civilians, and some protests and riots), demonstrations (comprising the remaining protests and riots), and strategic developments.

We focus on social unrest captured by demonstrations, typically (but not necessarily) consisting of protests and riots. While most protests and riots fall under demonstrations, not all are captured by it. More violent forms of riots are instead classified as political violence. Conversely, any event classified as a demonstration is either a protest or a riot. As a result, the combined number of protests and riots exceeds the number of demonstrations in our sample (see Figure 1 for the geographic locations of incidents of social unrest over the study period). Because we focus on specific markets and time frames within each market, our analysis only accounts for just under 10% of reported incidents of social unrest across Africa (see Appendix Figures B2 and B3).

3.3 Additional Variables

In linking price shocks with conflict, we aim to gain better insight into the motives behind this relationship by examining the prevalence of crop agriculture—specifically maize production—and the extent of inequalities in maize production within the market catchment zone. Using the 2010 snapshot of maize harvest area from the Spatial Production Allocation Model (IFPRI, 2019), we calculate the proportion of maize harvest area as the ratio of average maize harvest area to the total area within the market catchment zone. We use this variable as a measure of maize suitability or dependence on maize agriculture.

We also calculate the proportion of maize harvest area within ethnic boundaries, as shown in Figure 1 (see also Appendix Figure B4). Figure 3 illustrates the contrast between market catchment zones with similar average maize cropland but markedly different maize production inequality profiles. The average maize production suitability in each of the two presented market catchment zones is comparable. However, Kitui (in Kenya) is homogeneous—fully contained within the boundaries of a single ethnic group—with no production inequality, whereas Anie (in Togo) is fragmented—includes six different ethnic groups—with substantial production inequality across ethnic groups comprising the market catchment zone.

Using these ethnic boundaries, and the 2010 snapshot of world population counts from Open Spatial Demographic Data and Research, better known as WorldPop (Tatem, 2017), we construct a Greenberg–Gini type of metric (e.g., Montalvo and Reynal-Querol, 2005; Esteban et al., 2012; Bertinelli et al., 2025) of maize production inequality as follows:

$$G_i = \sum_{j=1}^{M_i} \sum_{k=1}^{M_i} \pi_{j,i} \pi_{k,i} d_{jk,i}, \tag{1}$$

where $\pi_{j,i}$ and $\pi_{k,i}$ are the population shares of ethnic groups j and k in the market catchment zone i. $d_{jk,i}$ is the distance measure, which in our case is the absolute difference in the proportions of maize cropland within the geographic boundaries of ethnic groups j and k in the market catchment zone i.

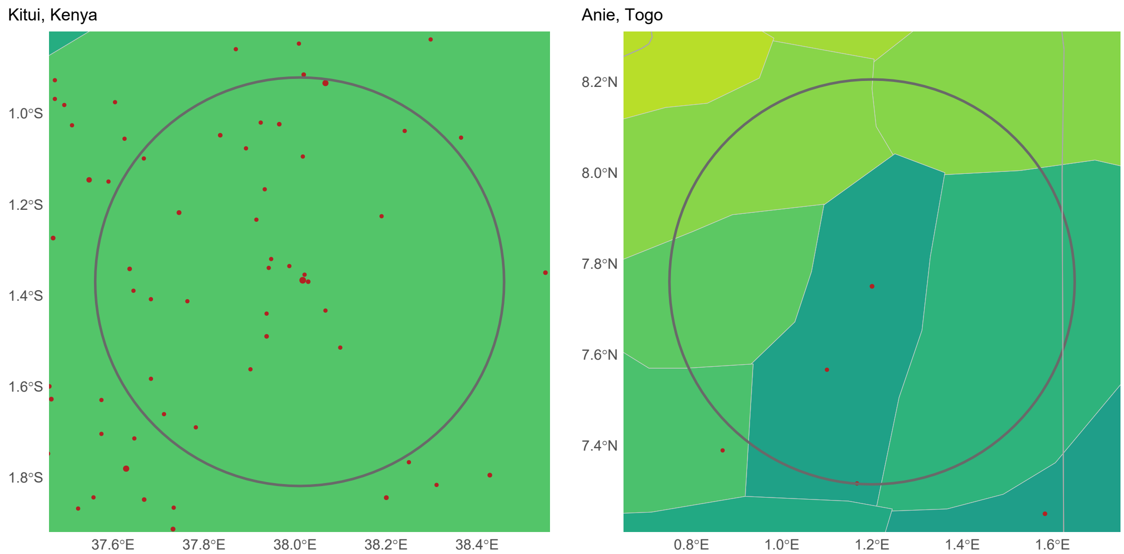

Figure 3: Average Cropland and Production Inequality Across Ethnic Boundaries

Note: Color-filled polygons depict the proportion of land allocated to maize production within ethnic boundaries. Ethnic boundary data are from the Murdock map (Murdock, 1959, 1967), and maize production data are from IFPRI (2019). Gray circles indicate market catchment zones. Red dots mark the locations of conflict incidents, based on data from ACLED (Raleigh et al., 2023).

3.4 Descriptive Statistics

We work with an unbalanced panel of 87 markets with varying lengths of price series over the period January 1997 to December 2024. Owing to our imposed lower-bound restriction, the minimum series length is 120 observations (10 years), while the maximum is 352 (over 29 years), with a mean of 223 and a standard deviation of 51. Overall, the dataset consists of 19,398 units of observations. Table 1 presents descriptive statistics of the key variables used in the analysis.

4 Empirical Strategy

In this section, we describe the model and outline our identification strategy. We denote a market with subscript i and a year-month with subscript t, and the unit of analysis is

Table 1: **Summary Statistics of Dependent and Independent Variables**

	Obs.	Mean	S.D.	Min	Max
Incidence of Social Unrest	19,398	0.150	0.357	0	1
Incidence of Protests	19,398	0.128	0.334	0	1
Incidence of Riots	19,398	0.099	0.299	0	1
Local price of maize (USD/kg)	19,398	0.384	0.165	0.040	1.370
Maize cropland proportion (A)	87	0.037	0.051	0.000	0.217
Production inequality (G)	87	0.005	0.011	0.000	0.082

Note: Data on conflict are from the ACLED Project (Raleigh et al., 2010, 2023). Data on maize cropland are from IFPRI (2019). Data on ethnic groups are from the Murdock map (Murdock, 1959, 1967). The conflict data correspond to the periods for which local price data are available over the January 1997–December 2024 time span. The cropland data correspond to the 2010 snapshot.

a market–year-month. For conflict exposure, we use a catchment zone defined as a 50-km radius circle centered on the market's geolocation.

4.1 Baseline Specification

Our preferred baseline specification is given by the following (second-stage) equation:

$$\text{CONFLICT}_{it} = \beta \text{PRICE}_{it} + \mu_i + \gamma_i t + \delta_i' \mathbf{d}_t + \varepsilon_{it}, \tag{2}$$

where CONFLICT_{it} denotes the conflict incidence observed in the catchment zone of market i in period t, and PRICE_{it} is the local price expressed in natural logarithms. The specification controls for time-invariant (or slowly evolving) differences across locations μ_i, location-specific linear trends $\gamma_i t$, and monthly seasonality $\delta_i' \mathbf{d}_t$. The error term is ε_{it}.

β is the coefficient of interest. A positive value implies that an increase in the price is associated with an increase in the probability of conflict. This association may be spurious, not least because conflict can disturb markets and thus lead to changes in prices.

To identify the coefficient of interest in equation (2) and address potential reverse causality, we instrument the potentially endogenous local maize price with the global maize price (e.g., Davis et al., 2025). Specifically, in the first stage, we estimate the following equation:

$$\text{PRICE}_{it} = \alpha\text{PRICE}_t + \kappa_i + \eta_i t + \theta_i'\mathbf{d}_t + \upsilon_{it}, \tag{3}$$

where PRICE_t is the natural logarithm of the global price in period t. As before, the specification controls for time-invariant (or slowly evolving) differences across locations κ_i, location-specific linear trends $\eta_i t$, and monthly seasonality $\theta_i'\mathbf{d}_t$. The error term is υ_{it}.

The identification relies on three assumptions: exogeneity, relevance, and exclusion. We discuss and justify each assumption below.

Exogeneity. Global maize prices are assumed to be exogenous to local maize prices and conflict. It is a plausible and widely accepted assumption that global maize prices are exogenous to local conflict and prices in Africa (Bazzi and Blattman, 2014; McGuirk and Burke, 2020; Ubilava et al., 2023), given that the continent accounts for only a small fraction of global maize production. For instance, Nigeria—the largest maize producer in our sample and the second largest in the region after South Africa—contributes less than 1% of global maize output (FAO, 2022).

Relevance. Global prices are assumed to be transmitted to local prices. Price transmission from global to local markets is notoriously equivocal and varies considerably across countries and markets. For example, Dillon and Barrett (2016) examine markets across East Africa and report an average elasticity of 0.42 for the local maize price with respect to the global maize price, ranging from 0.22 in Kenya to 0.82 in Ethiopia. Similarly, Baquedano and Liefert (2014) analyze price transmission at the country level and find that although local markets tend to be integrated with global markets, the aggregate (cross-country) elasticity of transmission is only 0.30 for maize; country-specific elasticities range from indistinguishable from 0 (e.g., Burkina Faso, Niger, and Zambia) to well above 0.5 (e.g., Malawi).

Exclusion. Global prices are assumed to affect conflict only through their impact on local prices. Global commodity price shocks can affect local conflict through multiple channels.

While the income–conflict literature generally agrees that the main effect of an international price change is on local prices and income (Dube and Vargas, 2013; Smith, 2014; Bazzi and Blattman, 2014; McGuirk and Burke, 2020), other pathways are possible. For example, international flows of food aid respond to price shocks (Nunn and Qian, 2014) and thereby amplify or mitigate conflict. International price shocks may also lead to greater within- and cross-country migration (Obi et al., 2020), which can result in conflict. Additionally, in some instances, higher international food prices allow the state to accrue higher tax revenues, which can be spent to reduce the onset of social unrest (Besley and Persson, 2010). However, because our study uses monthly data and focuses on narrowly defined geographic regions, we argue that within a given year-month, international maize prices cannot substantially influence local social unrest events through any channel other than local maize prices.

Overall, international maize prices satisfy the relevance requirement, and it can be plausibly argued that they meet both the exogeneity and exclusion conditions. Under these identifying assumptions, β captures an estimate of the local average treatment effect of maize prices on conflict. That is, it reflects the effect of local prices on conflict when changes in international maize prices manifest into changes in local maize prices.

4.2 Main Specification

While equation (2) allows us to examine whether changes in prices are associated with changes in conflict, it does not distinguish between the various channels through which local prices may influence local conflict. This distinction is crucial not only because understanding the underlying mechanisms can have important policy implications but also because the effects operating through different channels may offset one another, possibly even leading to an apparent "null" result when multiple mechanisms link prices—and, specifically, price-induced income shocks—to conflict.

We therefore focus on two related but distinct channels: income and income inequality. We posit that a price increase will, on average, have a positive income effect in areas more suitable for maize production and a polarizing income effect in heterogeneous areas—whether due to geological or ethnic differences—in terms of maize production. Accordingly, we augment the baseline specification as follows:

$$\text{CONFLICT}_{it} = \beta_1 \text{PRICE}_{it} + \beta_2 \text{PRICE}_{it} \times \text{A}_i + \beta_3 \text{PRICE}_{it} \times \text{G}_i + \mu_i + \lambda_i t + \delta_i' \mathbf{d}_t + \varepsilon_{it}, \quad (4)$$

where A_i is the proportion of land allocated to maize production within the market catchment zone i. As defined above, G_i represents maize production inequality in zone i. The rest of the variables are the same as in equation (2).

β_1 measures the effect of local maize prices on social unrest in areas with no cropland and no inequality in maize production. β_2 captures the differential effect of prices on conflict in areas with greater agricultural dependence (as measured by the proportion of cropland), relative to areas with little or no cropland. A negative estimate would suggest that rising prices reduce conflict in more agricultural areas, consistent with the notion that producer gains from higher prices dampen unrest—or, equivalently, that losses from lower prices amplify grievances. β_3 reflects the differential effect of prices on conflict in areas with greater inequality in maize production, relative to more homogeneous areas. A positive estimate would indicate that price increases are more likely to trigger conflict where agricultural production is unequally distributed across groups, consistent with the relative deprivation hypothesis that unequal access to agricultural rents amplifies distributional tensions.

5 Results

5.1 Baseline Results

Table 2 presents the baseline regression results. Column (1) reports results for social unrest, categorized as the disorder type "Demonstrations" in ACLED. Columns (2) and (3) show results for protests and riots, respectively—two specific manifestations of social unrest categorized as the event types “Protests” and “Riots” in ACLED. Disaggregating the results in this way allows us to investigate whether the overall relationship between local maize prices and social unrest is common to both types of unrest or varies by event type. Because riots in particular may capture forms of violence not included in social unrest, this disaggregation is potentially more nuanced than a simple data subsetting.

Table 2: Maize Prices and Social Unrest

	Dependent variable:		
	Social Unrest	Protests	Riots
	(1)	(2)	(3)
Independent variable:			
PRICE	−0.100***	−0.062	−0.044
	(0.033)	(0.038)	(0.033)
Fixed effects:			
Market	Y	Y	Y
Market-specific trend	Y	Y	Y
Market-specific seasonality	Y	Y	Y
Weak instrument test:			
Kleibergen-Paap rk Wald F	53.65	53.65	53.65
Sample size and goodness-of-fit:			
Observations (market-months)	19,398	19,398	19,398
Markets	87	87	87
R^2 (adjusted)	0.329	0.317	0.275
Additional calculations:			
Dependent variable mean	0.150	0.128	0.099

Note: The dependent variable is the incidence of conflict, and PRICE denotes the natural logarithm of the local maize price. PRICE is instrumented by the natural logarithm of the global maize price in the first stage. Values in parentheses are Conley (1999) standard errors, allowing for spatial correlation within a 500-km radius. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

The results in column (1) indicate that a 1% increase in the local maize price reduces the probability of social unrest by 0.10 percentage points. Given that the unconditional mean for the incidence of social unrest is 0.15, this result implies that a 10% price increase (which would be approximately equivalent to an average absolute monthly change in prices across all markets) is associated with a 6.67% reduction ($-0.10/0.15 \times 10\% = -6.67\%$) in the probability of social unrest, on average. Columns (2) and (3), which present event-specific estimates, provide quantitatively similar results for protests and riots, though both coefficients are noisy estimates and thus indistinguishable from zero.

Overall, these results align with the theoretical prediction that when local maize prices increase, both net producers and those employed in the agricultural supply chain stand to benefit economically. Higher maize prices raise farm revenue, thus reducing grievances. Given that a substantial proportion of the population in sub-Saharan Africa are employed in agriculture, one would expect these consequences to be far-reaching. Furthermore, a positive economic shock associated with an increase in the price of a commodity increases the opportunity cost of participating in potentially disruptive activities such as protests and riots, thereby reducing the incidence of such events.

Our findings differ from closely related studies on the effects of food price shocks on conflict and social unrest (Smith, 2014; Bellemare, 2015; De Winne and Peersman, 2021), which generally report a positive relationship. Focusing on studies of social unrest, although both Smith (2014) and Bellemare (2015) use monthly data, their empirical frameworks differ in important ways. Bellemare (2015) adopts a country-level approach, which likely over-represents urban areas, while Smith (2014) restricts his analysis to urban locations, where households are primarily net consumers of food. For such households, rising food prices erode real incomes, intensify food insecurity, and fuel economic grievances that can lead to unrest (Hendrix and Haggard, 2015). In contrast, by focusing on a sample of markets with varying degrees of agricultural dependence, our analysis not only dampens the effect of relative deprivation—at least in its temporal dimension, as higher prices benefit net producers—but also amplifies an opposing mechanism, specifically through the increased opportunity cost of protesting (e.g., Guardado and Pennings, 2025; Hastings and Ubilava, 2025).

5.2 Main Results

We suggest two possible channels through which the intensity of local maize production can shape the price–conflict relationship. First, by reducing deprivation relative to the recent past and by increasing the opportunity cost of unrest, a price increase should decrease social unrest in locations with more maize cropland (relative to those with little or none). Second, by heightening deprivation relative to others—which may foster resentment—a price increase should raise social unrest in locations where it may amplify income inequality across ethnically diverse groups (relative to more ethnically homogeneous areas).

We test these predictions by interacting prices with maize cropland proportion (suitability) and maize production inequality across ethnic lines (inequality), as specified in equation (4). This leads to our main results, presented in Table 3. Several features of interest emerge. First, as expected, the negative relationship between prices and social unrest is more pronounced in locations with a higher proportion of maize cropland; this is particularly true for riots. Second, maize production inequality exerts a positive differential effect on the relationship between prices and social unrest, also especially for riots. This effect is substantial: in locations with modest (though necessarily positive, as inequality cannot otherwise be defined) maize cropland but substantial inequality in maize production across ethnic boundaries, higher prices increase social unrest.

To provide context for the estimated coefficients, in locations with no maize cropland, a 10% increase in the local maize price is associated with a 7.5% reduction ($-0.113/0.150 \times 10\% = -7.5\%$) in the probability of social unrest relative to its baseline. This effect is further amplified in homogeneous locations with substantial maize cropland and muted—or even reversed—in locations with a high degree of maize production inequality. These differential effects are somewhat noisy for social unrest, and for protests in particular, but are much more precisely estimated for riots. Specifically, in locations at the 75th percentile of maize cropland share relative to those at the 25th percentile, a 10% increase in local maize prices corresponds to an additional 8.0% reduction ($-0.293 \times (0.055 - 0.001) \times 5/0.099 \times 10\% \approx -8.0\%$, where 5 is the scaling factor for cropland proportion as used in the regressions, chosen so that the maximum observed value was approximately one) in the probability of riots. Likewise, in locations at the 75th percentile of maize production inequality across ethnic boundaries

Table 3: Maize Prices, Production Suitability and Inequality, and Social Unrest

	Dependent variable:		
	Social Unrest	Protests	Riots
	(1)	(2)	(3)
Independent variables:			
PRICE	-0.113^{**}	-0.085^{**}	-0.039
	(0.046)	(0.042)	(0.037)
PRICE × A	-0.134	-0.083	-0.293^{**}
	(0.106)	(0.136)	(0.148)
PRICE × G	0.651^{*}	0.628^{*}	0.911^{***}
	(0.397)	(0.374)	(0.351)
Fixed effects:			
Market	Y	Y	Y
Market-specific trend	Y	Y	Y
Market-specific seasonality	Y	Y	Y
Sample size and goodness-of-fit:			
Observations (market-months)	19,398	19,398	19,398
Markets	87	87	87
R^2 (adjusted)	0.335	0.320	0.278
Additional calculations:			
Dependent variable mean	0.150	0.128	0.099

Note: The dependent variable is the incidence of conflict. PRICE denotes the natural logarithm of the local maize price. A is the maize production suitability index, which is the proportion of landmass used for maize production in the market catchment zone, scaled by a factor of 5 so that $A = 1$ corresponds to a location with approximately the maximum maize cropland proportion observed in the sample. G is the maize production inequality index, defined in equation (1), scaled by a factor of 12 so that $G = 1$ represents a location with approximately the maximum degree of production inequality across ethnic boundaries in the sample. Values in parentheses are Conley (1999) standard errors, allowing for spatial correlation within a 500-km radius. *** indicates statistical significance at the 0.01 level.

relative to those at the 25th percentile, a 10% increase in local maize prices corresponds to an additional 6.6% increase ($0.911 \times (0.006 - 0) \times 12/0.099 \times 10\% \approx 6.6\%$, where 12 is the scaling factor for maize production inequality, chosen so that the maximum observed value was approximately one) in the probability of riots.

5.3 Robustness Checks

A series of additional regressions, across alternative model specifications and data subsets, largely corroborate the parameter estimates presented in Table 3. We describe and summarize these robustness checks below.

First, we test whether our results are sensitive to the choice of dependent variable. Instead of using conflict incidence, as we do in the main specification, we re-estimate the model using the count of conflict events, normalized either by land area of the market catchment zone (to account for locations near large bodies of water) or by population (to account for the possibility of more conflict in more populous areas). The results remain broadly consistent with the main findings. Following a price increase, social unrest decreases, with the effect on riots particularly pronounced in markets with substantial maize agriculture. Moreover, social unrest, especially riots, increases in markets with substantial ethnic heterogeneity in maize production (Appendix Table A1).

Second, we examine whether our inference is sensitive to the method of clustering standard errors. In the main specification, we follow Conley (1999) and allow for spatial correlation within a 500-km radius. As a robustness check, we cluster standard errors at the market and country level. In both cases, the inference remains similar to that of the main findings (Appendix Table A2).

Third, we test the sensitivity of our results to the definition of a market catchment zone and to the minimum length of the price series. In the main analysis, we define catchment zones as a 50-km radius around the market centroid and require a minimum time series length of 120 months. In the robustness checks, we (i) expand catchment zones to a 100-km radius, and (ii) increase the minimum series length to 180 months. In both cases, the results closely mirror the main findings (Appendix Table A3).

Fourth, we test the sensitivity of our results to the omission of observations that may overlap with other crops or economic activities. Specifically, we omit markets where (i) either wheat or sorghum—two other major cereal crops—have larger cropland areas within the market catchment zone, or (ii) at least one mining site is located in the market catchment zone.[1] In both cases, the results are comparable to, or even stronger than, the main results of this study (Appendix Table A4).

Finally, we conduct a falsification test using one-year lags and leads of prices to verify that our results are not driven by spurious trends. If the main results are valid, then (after controlling for the contemporaneous regressors in the baseline specification) neither the lagged nor the lead price variables, or their interactions, should exhibit a meaningful relationship with conflict. Consistent with this expectation, we find no statistically significant lag or lead effects on any form of social unrest (Appendix Table A5).

5.4 Mechanisms

Our main results suggest two contrasting effects. First, in regions where a substantial proportion of land is allocated to maize production, an increase in the maize price (i.e., a likely positive income shock) decreases the probability of social unrest, plausibly by improving perceptions of well-being relative to the recent past and by raising the opportunity cost of protesting. Second, in fragmented regions, specifically where fragmentation is manifested through inequalities in maize production, an increase in the maize price increases the probability of social unrest—riots in particular—as it likely amplifies resentment among ethnic groups that are disproportionately affected by the price change. In what follows, we test these mechanisms.

[1] As with maize, we obtain wheat and sorghum cropland areas from IFPRI (2019). Mine locations are sourced from the International Council on Mining and Metals (ICMM) Global Mining Dataset, available at https://www.icmm.com/en-gb/research/data/2025/global-mining-dataset.

5.4.1 Seasonality of Conflict

To begin, we test whether the effect varies with the time of year relative to the harvest. Because much of agriculture in Africa is at a subsistence level, any income changes linked to the harvest will likely manifest during the early months of the crop year (Ubilava et al., 2023). Likewise, the opportunity cost of conflict is likely heightened during the harvest months (Guardado and Pennings, 2025; Hastings and Ubilava, 2025). If our suggested mechanisms are valid—that is, if a price increase reduces social unrest through income gains in regions with substantial maize agriculture and increases social unrest through income inequalities in regions characterized by disparities in maize production—then these effects should be most pronounced at or shortly after harvest.

We operationalize this test by interacting the regressors in equation (4) with a postharvest dummy variable that equals one during the three consecutive months beginning with the start of harvest, and zero otherwise. The results, presented in Table 4, show that the differential effect during the postharvest season is negative in locations with a heterogeneous propensity to cultivate maize. Protests drive this effect. Put differently, for relatively more peaceful forms of social unrest, such as protests, a positive relationship between prices and conflict manifests largely outside the harvest/postharvest period; during the postharvest period, the opportunity cost of conflict likely mutes this relationship (Guardado and Pennings, 2025; Hastings and Ubilava, 2025). In the case of more violent forms of unrest—riots—we do not observe a seasonal decrease in conflict, presumably suggesting that the motives driving such conflict are not influenced by rising opportunity costs at harvest time, and possibly that predatory behavior—which can be linked with relative abundance (Koren, 2018; Ubilava et al., 2023)—offsets any "gains" in conflict mitigation achieved by higher opportunity costs.

5.4.2 Growing-Season Rainfall

Next, we test whether the effect varies by harvest quality by interacting the relevant set of regressors in equation (4) with local rainfall observed during the maize growing season

Table 4: Maize Prices and Social Unrest During the Early Postharvest Season

	Dependent variable:		
	Social Unrest	Protests	Riots
	(1)	(2)	(3)
Independent variables:			
PRICE	−0.123**	−0.104**	−0.029
	(0.053)	(0.049)	(0.041)
PRICE × A	−0.186*	−0.111	−0.266**
	(0.102)	(0.145)	(0.126)
PRICE × G	0.815*	0.809**	0.900***
	(0.426)	(0.404)	(0.332)
PRICE × H	0.039	0.075	−0.041
	(0.048)	(0.056)	(0.034)
PRICE × A × H	0.178	0.091	−0.086
	(0.122)	(0.136)	(0.077)
PRICE × G × H	−0.607***	−0.670***	0.026
	(0.143)	(0.167)	(0.128)
Fixed effects:			
Market	Y	Y	Y
Market-specific trend	Y	Y	Y
Market-specific seasonality	Y	Y	Y
Sample size and goodness-of-fit:			
Observations (market-months)	19,398	19,398	19,398
Markets	87	87	87
R^2 (adjusted)	0.325	0.313	0.267
Additional calculations:			
Dependent variable mean	0.150	0.128	0.099

Note: The dependent variable is the incidence of conflict. PRICE denotes the natural logarithm of the local maize price. A is the maize production suitability index, which is the proportion of landmass used for maize production in the market catchment zone, scaled by a factor of 5 so that $A = 1$ corresponds to a location with approximately the maximum maize cropland proportion observed in the sample. G is the maize production inequality index, defined in equation (1), scaled by a factor of 12 so that $G = 1$ represents a location with approximately the maximum degree of production inequality across ethnic boundaries in the sample. H is a postharvest dummy variable that equals one during the three consecutive months beginning with the start of harvest, and zero otherwise. Values in parentheses are Conley (1999) standard errors, allowing for spatial correlation within a 500-km radius. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

within the market catchment zone. We use rainfall rather than yield because reliable data on the latter are not available and yield can be endogenous to conflict (Koren, 2018). We rely on rainfall rather than temperature as the former is the most likely determinant of local crop yields, especially across Africa (McGuirk and Nunn, 2025).

If our suggested mechanism is valid, then in years following plausibly bad harvests—because of below- or above-average rainfall during the growing season (Hendrix and Salehyan, 2012; Hastings and Ubilava, 2025)—the differential effects associated with maize cropland proportion and maize production inequality should be attenuated to zero. We operationalize this test as follows. First, for each market catchment zone, we calculate monthly averages of daily rainfall using data from the National Oceanic and Atmospheric Administration's Climate Prediction Center over the 1979–2024 period.[2] Then, for each calendar month, we obtain deviations from the average rainfall in that month. Specifically, for each market catchment zone i and month m in period t, we compute standardized measures of rainfall deviation as $\tilde{r}_{it}^{(m)} = \left(r_{it}^{(m)} - \mu_i^{(m)}\right)/\sigma_i^{(m)}$, where $\mu_i^{(m)}$ and $\sigma_i^{(m)}$ are the mean and standard deviation of rainfall observed in market catchment zone i in calendar month m. Finally, using $\tilde{r}_{it}^{(m)}$, we construct a measure of suboptimal weather during the growing season (defined as the months from the beginning of the planting season until, but not including, the beginning of the harvest season) by taking the average value of the rainfall deviations from the long-term trend over the growing-season months:

$$R_{it} = \frac{1}{|S|}\sum_{m\in S}\tilde{r}_{it}^{(m)}, \tag{5}$$

where S is the set of months comprising the growing season and $|S|$ is the number of months in the growing season.

We then estimate an augmented regression by interacting the absolute value of R_{it} with the original set of regressors in equation (4). Table 5 presents the results. The differential

[2]The data are from the Global Unified Gauge-Based Analysis of Daily Precipitation, available at https://psl.noaa.gov/data/gridded/data.cpc.globalprecip.html.

effect of adverse weather during the growing season is negative both in locations with substantial maize agriculture and in those with a heterogeneous propensity to cultivate maize, with the effect being more pronounced in the latter. This suggests that in crop years with poor harvests, an increase in maize prices leads to relatively little change in income inequality—presumably because net producers cannot realize substantial surplus income from sales—and thus generates muted grievances, consistent with the relative deprivation hypothesis. That said, these effects are small and largely indistinguishable from zero, in part because our measure of adverse weather is likely a noisy proxy for harvest outcomes.

5.4.3 Afrobarometer Surveys

The previous two tests produced results consistent with our hypotheses, but the evidence is arguably weak and equivocal. Both tests are also somewhat speculative, as we do not directly observe changes in people's income or in income inequality.

To address these limitations, we turn to geolocated survey data from Afrobarometer. Specifically, we use a subset of relevant variables from survey rounds 2 through 9 and merge them with our main dataset to identify respondents located in areas for which we have price data. Because Afrobarometer covers only a subset of African countries, this procedure leaves us with 69 (of 87) markets across 12 (of 18) countries. The time coverage is from August 2002 to April 2023. The remaining sample includes most of the conflict-prone countries in our original sample—with notable omissions of South Sudan and Somalia—and the key episodes of major price swings during the study period.

First, we examine the relationship between maize prices and individual well-being, considering both absolute and relative measures of self-reported well-being. The absolute measure comes from the survey question "How would you describe your own present living conditions?" And the relative measure refers to the question "How do you rate your living conditions compared to those of other [people in your country]?" In both cases, responses are ordered from 1 ("Very bad") to 5 ("Very good").

Table 5: Maize Prices and Social Unrest in the Wake of Growing-Season Rainfall

	Dependent variable:		
	Social Unrest	Protests	Riots
	(1)	(2)	(3)
Independent variables:			
PRICE	−0.115**	−0.090**	−0.042
	(0.047)	(0.045)	(0.039)
PRICE × A	−0.130	−0.072	−0.314**
	(0.117)	(0.131)	(0.138)
PRICE × G	0.666	0.633	0.962**
	(0.425)	(0.398)	(0.375)
PRICE × R	0.009	0.015	0.010
	(0.010)	(0.012)	(0.009)
PRICE × A × R	−0.011	−0.028	0.046
	(0.071)	(0.056)	(0.055)
PRICE × G × R	−0.096	−0.050	−0.219*
	(0.129)	(0.114)	(0.122)
Fixed effects:			
Market	Y	Y	Y
Market-specific trend	Y	Y	Y
Market-specific seasonality	Y	Y	Y
Sample size and goodness-of-fit:			
Observations (market-months)	19,398	19,398	19,398
Markets	87	87	87
R^2 (adjusted)	0.335	0.320	0.278
Additional calculations:			
Dependent variable mean	0.150	0.128	0.099

Note: The dependent variable is the incidence of conflict. PRICE denotes the natural logarithm of the local maize price. A is the maize production suitability index, which is the proportion of landmass used for maize production in the market catchment zone, scaled by a factor of 5 so that $A = 1$ corresponds to a location with approximately the maximum maize cropland proportion observed in the sample. G is the maize production inequality index, defined in equation (1), scaled by a factor of 12 so that $G = 1$ represents a location with approximately the maximum degree of production inequality across ethnic boundaries in the sample. R is the absolute alue of the market-specific growing-season average of standardized monthly rainfall deviations. Values in parentheses are Conley (1999) standard errors, allowing for spatial correlation within a 500-km radius. **, and * indicate statistical significance at the 0.05, and 0.10 levels, respectively.

To account for the differential effect that an agricultural commodity price change can have on groups of people who may be harmed or benefit from such a change, we interact the price with a dummy variable that equals one if a person lists agriculture (or a related field) as their main occupation, and zero otherwise. For each of the two dependent variables described above, we estimate the following equation:

$$\mathrm{Y}_{rit} = \beta_1 \mathrm{PRICE}_{it} + \beta_2 \mathrm{PRICE}_{it} \times \mathrm{F}_{rit} + \mu_i + \lambda_t + \varepsilon_{rit}, \tag{6}$$

where Y_{rit} is the respondent-specific outcome variable observed in market catchment zone i in period t, and F_{rit} is a binary variable depicting the respondent's employment in the agricultural sector. As before, PRICE_{it} denotes the natural logarithm of the market-specific maize price, and μ_i and λ_t represent location- and time-specific fixed effects, respectively. εrit is the error term. In this specification, reverse causality is not a concern for identification: local prices can be treated as exogenous to individual well-being, and hence the instrumental variable approach is no longer required.

However, not all agriculture is maize agriculture. To capture the differential effect of employment in maize agriculture, where most of the benefits from rising maize prices would accrue, we introduce the proportion of maize cropland in the market catchment zone as an interaction term in equation (6):

$$\begin{aligned} \mathrm{Y}_{rit} = {} & \beta_1 \mathrm{PRICE}_{it} + \beta_2 \mathrm{PRICE}_{it} \times \mathrm{F}_{rit} \\ & + \beta_3 \mathrm{PRICE}_{it} \times \mathrm{A}_i + \beta_4 \mathrm{PRICE}_{it} \times \mathrm{F}_{rit} \times \mathrm{A}_i + \mu_i + \lambda_t + \varepsilon_{rit}. \end{aligned} \tag{7}$$

Thus, for each of the two measures of individual well-being, we estimate two sets of coefficients, with and without interaction with the proportion of maize cropland in the market catchment zone. Table 6 presents the results, from which several encouraging features of interest emerge. First, maize price increases improve the well-being of those employed in the agricultural sector; second, this effect is amplified in locations with maize agriculture; and third, the effect is most pronounced in regressions with the relative measure of well-being as the dependent variable, consistent with the relative deprivation hypothesis. Overall, these results support the suggestive evidence presented in the previous sections of the paper.

Table 6: Maize Prices and Individual Well-Being

	Dependent variable:			
	Well-being (absolute)		Well-being (relative)	
	(1)	(2)	(3)	(4)
Independent variables:				
PRICE	−0.094	−0.212	−0.262**	−0.491*
	(0.142)	(0.205)	(0.123)	(0.287)
PRICE × F	0.132***	0.115***	0.145***	0.082***
	(0.031)	(0.033)	(0.030)	(0.023)
PRICE × A		0.234		0.481
		(0.165)		(0.323)
PRICE × F × A		0.032		0.121**
		(0.096)		(0.059)
Fixed effects:				
Market	Y	Y	Y	Y
Period	Y	Y	Y	Y
Sample size and goodness-of-fit:				
Observations (respondent-months)	21,689	21,689	12,053	12,053
Markets	69	69	66	66
R^2 (adjusted)	0.112	0.112	0.097	0.098
Additional calculations:				
Dependent variable mean	2.591	2.591	2.817	2.817
Dependent variable range	[1; 5]	[1; 5]	[1; 5]	[1; 5]

Note: The dependent variable is a categorical outcome ranging from "Very bad" to "Very good." PRICE denotes the natural logarithm of the local maize price. F measures agricultural employment. A is the proportion of landmass used for maize production in the market catchment zone, scaled by a factor of 5 so that $A = 1$ corresponds to a location with approximately the maximum maize cropland proportion observed in the sample. Values in parentheses are Conley (1999) standard errors, allowing for spatial correlation within a 500-km radius. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Next, using individual-specific information on respondents' occupational and ethnic backgrounds, we calculate measures of agricultural dependence and inequality. For agricultural dependence, we simply obtain the proportion of respondents, within each survey round, who listed agriculture or farming as their main occupation. We denote this variable by $A_{i,s}$. We compute inequality using a formula similar to that in the main specification:

$G_{i,s} = \sum_{j=1}^{M_{i,s}} \sum_{k=1}^{M_{i,s}} \pi_{j,i,s}\pi_{k,i,s}d_{jk,i,s}$, where $M_{i,s}$ is the total number of unique ethnic groups within the market catchment zone i observed in survey round s; $\pi_{j,i,s}$ and $\pi_{k,i,s}$ denote the proportion of respondents from a given ethnicity; and $d_{jk,i,s}$ is the distance measure, in this case, the absolute difference in the proportions of agricultural dependence within ethnic groups j and k in the market catchment zone i in survey round s.

Using the same two dependent variables as before, we estimate the following equation:

$$\mathrm{Y}_{rit} = \beta_1\mathrm{PRICE}_{it} + \beta_2\mathrm{PRICE}_{it} \times \mathrm{A}_{i,s} + \beta_3\mathrm{PRICE}_{it} \times \mathrm{G}_{i,s} + \mu_i + \lambda_t + \varepsilon_{rit}. \tag{8}$$

This equation mimics the main specification but departs from it in several ways: (i) the unit of measurement is respondent/year-month rather than market/year-month; (ii) the measures of agricultural dependence and inequality vary over time, by survey round; and (iii) the measures of agricultural dependence and inequality are not specific to maize agriculture (even though the price is for maize). Table 7 presents the results, providing further support for the suggestive evidence that price increases improve well-being—particularly relative well-being—in locations with a higher share of agricultural employment. At the same time, they tend to reduce well-being, albeit not significantly, in locations with substantial inequality in agricultural employment across ethnic groups.

Finally, to establish equivalence between the main results of this study and the mechanism test presented here, we estimate the following equation:

$$\mathrm{CONFLICT}_{rit} = \beta_1\mathrm{PRICE}_{it} + \beta_2\mathrm{PRICE}_{it} \times \mathrm{A}_i + \beta_3\mathrm{PRICE}_{it} \times \mathrm{G}_i + \mu_i + \lambda_t + \varepsilon_{rit}, \tag{9}$$

where $\mathrm{CONFLICT}_{rit}$ is a binary dependent variable that equals one if a respondent identified either "Political instability/Ethnic tensions" or "Political violence" as the most important problem facing their country. The results, presented in Table 8, align with anecdotal evidence as well as the expected effects of a price increase. In locations with little or no maize agriculture, rising prices lead to political instability and ethnic tensions, making political

Table 7: Maize Prices, Agricultural Dependence and Inequality, and Well-Being

	Dependent variable:	
	Well-being (absolute)	Well-being (relative)
	(1)	(2)
PRICE	−0.092	−0.452***
	(0.165)	(0.166)
PRICE × A^{ab}	0.118*	0.345***
	(0.063)	(0.128)
PRICE × G^{ab}	−0.069	−0.174
	(0.103)	(0.129)
Fixed effects:		
Market	Y	Y
Period	Y	Y
Sample size and goodness-of-fit:		
Observations (respondent-months)	21,767	12,098
Markets	69	66
R^2 (adjusted)	0.110	0.095
Additional calculations:		
Dependent variable mean	2.592	2.816
Dependent variable range	[1; 5]	[1; 5]

Note: The dependent variable is a categorical outcome ranging from "Very bad" to "Very good." PRICE denotes the natural logarithm of the local maize price. A^{ab} measures agricultural dependence (i.e., the proportion of individuals within the market catchment zone employed in agriculture) scaled by a factor of 2 such that $A^{ab} = 1$ corresponds to a location with approximately the maximum value observed in the sample. G^{ab} is the measure of agriculture-specific occupational inequality across ethnic groups, scaled by a factor of 3 so that $G^{ab} = 1$ corresponds to a location with approximately the maximum observed value of this measure. Values in parentheses are Conley (1999) standard errors, allowing for spatial correlation within a 500-km radius. ***, and * indicate statistical significance at the 0.01, and 0.10 levels, respectively.

instability and ethnic tensions the key problem to address from the perspective of people who may be affected by these problems. This effect is mitigated, if not reversed, in areas with maize cultivation, suggesting that price decreases there are more likely to trigger unrest. Consistent with our main findings, the effect is amplified in locations with substantial inequality in maize production across ethnic groups. The effects are smaller and statistically indistinguishable from zero for political violence, reinforcing that these findings should not be generalized across all forms of conflict.

Table 8: Maize Prices, Suitability and Inequality, and Social Unrest

	Dependent variable:	
	Unrest	Violence
	(1)	(2)
PRICE	0.036***	−0.002
	(0.012)	(0.009)
PRICE × A	−0.067***	−0.016*
	(0.019)	(0.008)
PRICE × G	0.026**	0.002
	(0.011)	(0.022)
Fixed effects:		
Market	Y	Y
Period	Y	Y
Sample size and goodness-of-fit:		
Observations (respondent-months)	20,999	20,999
Markets	69	69
R^2 (adjusted)	0.041	0.013
Additional calculations:		
Dependent variable mean	0.029	0.010

Note: The dependent variable is a binary outcome indicating if a respondent listed "Political instability/Ethnic tensions" (unrest) or "Political violence" (violence) as the most important problem facing their country. PRICE denotes the natural logarithm of the local maize price. A is the maize production suitability index, which is the proportion of landmass used for maize production in the market catchment zone, scaled by a factor of 5 so that $A = 1$ corresponds to a location with approximately the maximum maize cropland proportion observed in the sample. G is the maize production inequality index, defined in equation (1), scaled by a factor of 12 so that $G = 1$ represents a location with approximately the maximum degree of production inequality across ethnic boundaries in the sample. Values in parentheses are Conley (1999) standard errors, allowing for spatial correlation within a 500-km radius. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

6 Conclusion

Do changes in local commodity prices cause social unrest? We study this question using data on local maize prices across 87 markets in 18 African countries and find that, indeed, higher maize prices reduce unrest—riots in particular—in areas with substantial maize agriculture, but increase unrest in regions where ethnic groups differ in their reliance on maize production. These effects vary with the timing of the crop year and across years with differing growing conditions, underscoring the role of realized income inequalities as the underlying mechanism.

We provide further evidence on the plausibility of this mechanism using an auxiliary set of results based on Afrobarometer survey data. Specifically, we show that increases in maize prices improve well-being—particularly the relative well-being of those employed in the agricultural sector. Using the same survey data, we find that higher maize prices are associated with a greater likelihood that respondents identify political instability and ethnic tensions as the most important problems facing their country in locations with little or no maize agriculture. This effect is mitigated, and eventually reverses, in areas with substantial maize production but is amplified in those characterized by high inequality in maize production across ethnic groups.

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A Tables

Table A1: Robustness Check: Using Incidents Instead of Incidence

	Dependent variable:					
	Incidents per 1,000,000 ha			Incidents per 1,000,000 people		
	Social Unrest	Protests	Riots	Social Unrest	Protests	Riots
	(1)	(2)	(3)	(4)	(5)	(6)
Independent variables:						
PRICE	−0.211	−0.170	0.066	−0.387**	−0.271*	−0.064
	(0.192)	(0.139)	(0.115)	(0.176)	(0.145)	(0.130)
PRICE × A	0.245	0.432	−0.262	0.128	0.248	−0.524
	(0.453)	(0.458)	(0.663)	(0.365)	(0.287)	(0.370)
PRICE × G	1.171	0.828	3.037***	1.521**	1.028*	2.062***
	(1.481)	(1.454)	(0.933)	(0.594)	(0.576)	(0.641)
Sample size and goodness-of-fit:						
Observations (market-months)	19,398	19,398	19,398	19,398	19,398	19,398
Markets	87	87	87	87	87	87
R^2 (adjusted)	0.451	0.448	0.408	0.185	0.226	0.082
Additional calculations:						
Dependent variable mean	0.506	0.394	0.268	0.451	0.356	0.221

Note: The dependent variable is the number of conflict incidents per million hectares (columns (1)–(3)) or per million people (columns (4)–(6)). PRICE denotes the natural logarithm of the local maize price. A is the proportion of landmass used for maize production in the market catchment zone, scaled by a factor of 5 so that $A = 1$ corresponds to a location with approximately the maximum maize cropland proportion observed in the sample. G is the maize production inequality index, defined in equation (1), scaled by a factor of 12 so that $G = 1$ represents a location with approximately the maximum degree of production inequality across ethnic boundaries in the sample. Values in parentheses are Conley (1999) standard errors, allowing for spatial correlation within a 500-km radius. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table A2: Robustness Check: Standard Error Clustering

	Social Unrest	Protests	Riots	Social Unrest	Protests	Riots
	(1)	(2)	(3)	(4)	(5)	(6)
	Clustering at the market level			Clustering at the country level		
Independent variables:						
PRICE	–0.113**	–0.085*	–0.039	–0.113**	–0.085**	–0.039
	(0.054)	(0.047)	(0.033)	(0.047)	(0.039)	(0.041)
PRICE × A	–0.134	–0.083	–0.293**	–0.134	–0.083	–0.293**
	(0.149)	(0.152)	(0.116)	(0.139)	(0.147)	(0.132)
PRICE × G	0.651*	0.628*	0.911**	0.651	0.628*	0.911**
	(0.378)	(0.377)	(0.373)	(0.382)	(0.349)	(0.348)
Sample size and goodness-of-fit:						
Observations (market-months)	19,398	19,398	19,398	19,398	19,398	19,398
Markets	87	87	87	87	87	87
R^2 (adjusted)	0.326	0.314	0.267	0.326	0.314	0.267
Additional calculations:						
Dependent variable mean	0.150	0.128	0.099	0.150	0.128	0.099

Note: Incidence of conflict is the dependent variable, and PRICE denotes the natural logarithm of the local maize price. A is the proportion of landmass used for maize production in the market catchment zone, scaled by a factor of 5 so that $A = 1$ corresponds to a location with approximately the maximum maize cropland proportion observed in the sample. G is the maize production inequality index, defined in equation (1), scaled by a factor of 12 so that $G = 1$ represents a location with approximately the maximum degree of production inequality across ethnic boundaries in the sample. Values in parentheses are standard errors clustered at the market or country level (columns (1)–(3) and columns (4)–(6), respectively). ** and * denote statistical significance at the 0.05 and 0.10 levels, respectively.

Table A3: Robustness Check: Catchment Zones and Series Lengths

	Social Unrest	Protests	Riots	Social Unrest	Protests	Riots
	(1)	(2)	(3)	(4)	(5)	(6)
	Large (100km radius)			Long (>180 observations)		
Independent variables:						
PRICE	–0.170	–0.145	–0.017	–0.171**	–0.131*	–0.069
	(0.114)	(0.100)	(0.078)	(0.075)	(0.067)	(0.044)
PRICE × A	–0.075	0.043	–0.538**	–0.070	–0.033	–0.267*
	(0.188)	(0.174)	(0.234)	(0.137)	(0.156)	(0.153)
PRICE × G	0.304	0.182	0.373*	0.810**	0.773**	1.031***
	(0.306)	(0.382)	(0.223)	(0.320)	(0.306)	(0.309)
Sample size and goodness-of-fit:						
Observations (market-months)	12,245	12,245	12,245	15,085	15,085	15,085
Markets	55	55	55	61	61	61
R^2 (adjusted)	0.380	0.375	0.327	0.328	0.316	0.279
Additional calculations:						
Dependent variable mean	0.245	0.212	0.171	0.165	0.139	0.113

Note: The dependent variable is the incidence of conflict in large (100-km radius) market catchment zones (columns (1)–(3)) or long (at least 180 observations) price series (columns (4)–(6)). PRICE denotes the natural logarithm of the local maize price. A is the proportion of landmass used for maize production in the market catchment zone, scaled by a factor of 7 in large market catchment zones, and by a factor of 5 in long price series so that $A = 1$ corresponds to a location with approximately the maximum maize cropland proportion observed in the sample. G is the maize production inequality index, defined in equation (1), scaled by a factor of 13 in large market catchment zones, and by a factor of 12 in long price series so that $G = 1$ represents a location with approximately the maximum degree of production inequality across ethnic boundaries in the sample. Values in parentheses are Conley (1999) standard errors, allowing for spatial correlation within a 500-km radius. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table A4: Robustness Check: Omitting markets with other major crops or mining sites

	Social Unrest	Protests	Riots	Social Unrest	Protests	Riots
	(1)	(2)	(3)	(4)	(5)	(6)
	Mostly maize			No mining site		
Independent variables:						
PRICE	–0.145	–0.113	–0.045	–0.120***	–0.086**	–0.049
	(0.088)	(0.086)	(0.077)	(0.045)	(0.043)	(0.034)
PRICE × A	–0.105	–0.053	–0.301*	–0.161	–0.114	–0.291**
	(0.148)	(0.174)	(0.179)	(0.107)	(0.134)	(0.146)
PRICE × G	0.752**	0.703**	0.995***	0.810**	0.774**	0.984***
	(0.363)	(0.350)	(0.331)	(0.343)	(0.323)	(0.337)
Sample size and goodness-of-fit:						
Observations (market-months)	12,029	12,029	12,029	18,193	18,193	18,193
Markets	52	52	52	82	82	82
R^2 (adjusted)	0.369	0.351	0.307	0.333	0.320	0.277
Additional calculations:						
Dependent variable mean	0.181	0.154	0.132	0.141	0.121	0.091

Note: The dependent variable is the incidence of conflict in market catchment zones where maize is the dominant cereal crop (columns (1)–(3)) or there is no mining site (columns (4)–(6)). PRICE denotes the natural logarithm of the local maize price. A is the proportion of landmass used for maize production in the market catchment zone, scaled by a factor of 5 so that $A = 1$ corresponds to a location with approximately the maximum maize cropland proportion observed in the sample. G is the maize production inequality index, defined in equation (1), scaled by a factor of 12 so that $G = 1$ represents a location with approximately the maximum degree of production inequality across ethnic boundaries in the sample. Values in parentheses are Conley (1999) standard errors, allowing for spatial correlation within a 500-km radius. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table A5: Robustness Check: 12-Month Lags and Leads

	Social Unrest	Protests	Riots	Social Unrest	Protests	Riots
	(1)	(2)	(3)	(4)	(5)	(6)
		12-month lag			12-month lead	
Independent variables:						
PRICE(lag)	0.195	0.163	0.015			
	(0.127)	(0.115)	(0.118)			
PRICE(lag) × A	0.294	0.110	0.032			
	(0.340)	(0.376)	(0.546)			
PRICE(lag) × G	–0.243	0.189	–0.369			
	(0.420)	(0.467)	(0.595)			
PRICE	–0.165*	–0.125	–0.032	0.097	0.114	–0.006
	(0.093)	(0.082)	(0.091)	(0.196)	(0.158)	(0.107)
PRICE × A	–0.304	–0.119	–0.336	0.137	–0.156	–0.397
	(0.221)	(0.198)	(0.437)	(0.636)	(0.726)	(0.720)
PRICE × G	0.596	0.308	1.105**	0.398	1.196	1.549**
	(0.420)	(0.364)	(0.522)	(0.689)	(0.768)	(0.636)
PRICE(lead)				–0.162	–0.150	–0.035
				(0.142)	(0.113)	(0.095)
PRICE(lead) × A				–0.186	0.080	0.101
				(0.456)	(0.495)	(0.570)
PRICE(lead) × G				0.185	–0.490	–0.541
				(0.624)	(0.625)	(0.511)
Sample size and goodness-of-fit:						
Observations (market-months)	18,354	18,354	18,354	18,354	18,354	18,354
Markets	87	87	87	87	87	87
R^2 (adjusted)	0.339	0.324	0.280	0.325	0.306	0.268
Additional calculations:						
Dependent variable mean	0.156	0.133	0.103	0.141	0.119	0.094

Note: Incidence of conflict is the dependent variable. PRICE denotes the natural logarithm of the local maize price, PRICE(lag) is the natural logarithm of the local maize price observed 12 months before, and PRICE (lead) is the natural logarithm of the local maize price observed 12 months after. A is the proportion of landmass used for maize production in the market catchment zone, scaled by a factor of 5 so that $A = 1$ corresponds to a location with approximately the maximum maize cropland proportion observed in the sample. G is the maize production inequality index, defined in equation (1), scaled by a factor of 12 so that $G = 1$ represents a location with approximately the maximum degree of production inequality across ethnic boundaries in the sample. Values in parentheses are Conley (1999) standard errors, allowing for spatial correlation within a 500-km radius. **, and * indicate statistical significance at the 0.05, and 0.10 levels, respectively.

B Figures

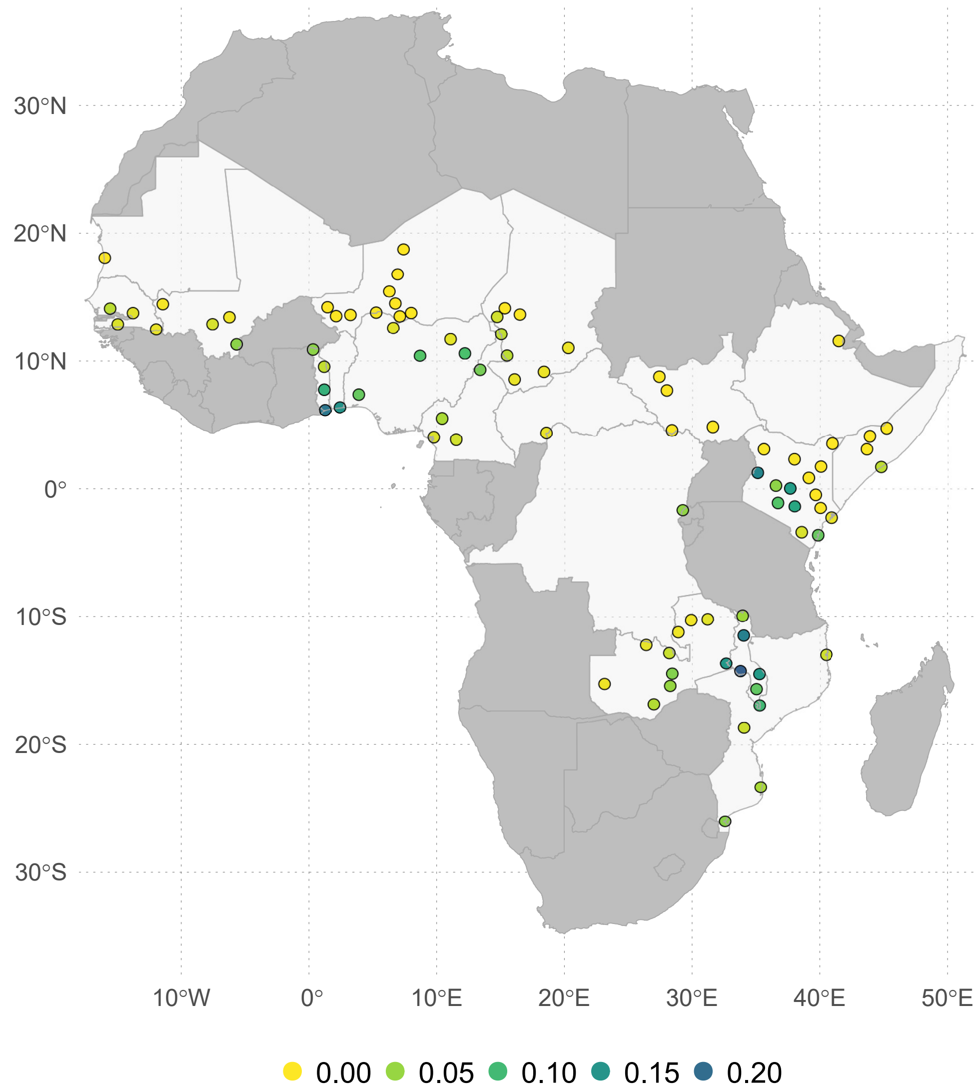

Figure B1: Maize Cropland Proportion in Market Catchment Zones

Note: Markets are identified from prices sourced from FEWS NET, GIEWS, and the WFP. Cropland proportions are calculated based on the maize harvest area obtained from IFPRI (2019).

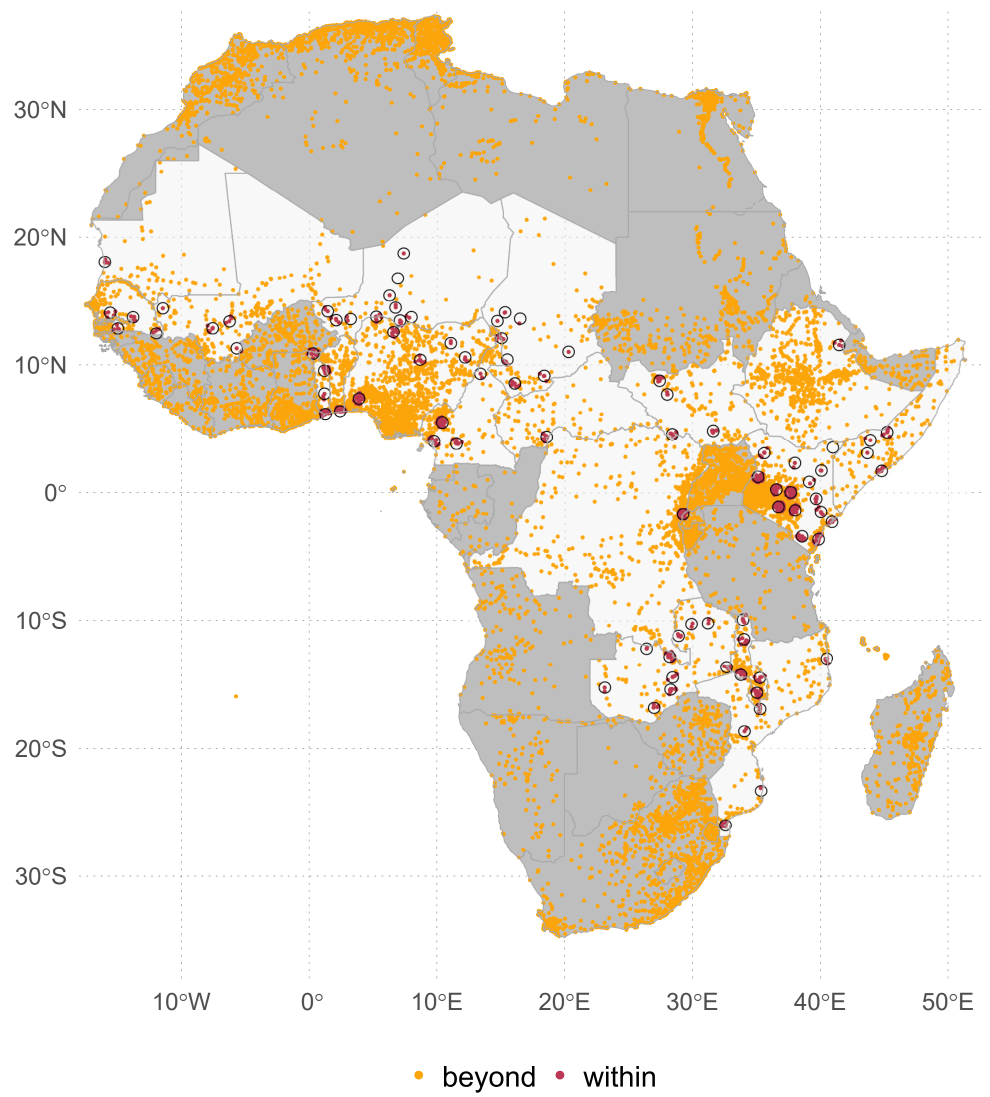

Figure B2: Conflict Within and Beyond Market Catchment Zones

Note: A market catchment zone is defined as an area within a 100-km radius of the market centroid. Incidents include battles, explosions/remote violence, violence against civilians, and protests or riots, as recorded in ACLED (Raleigh et al., 2023).

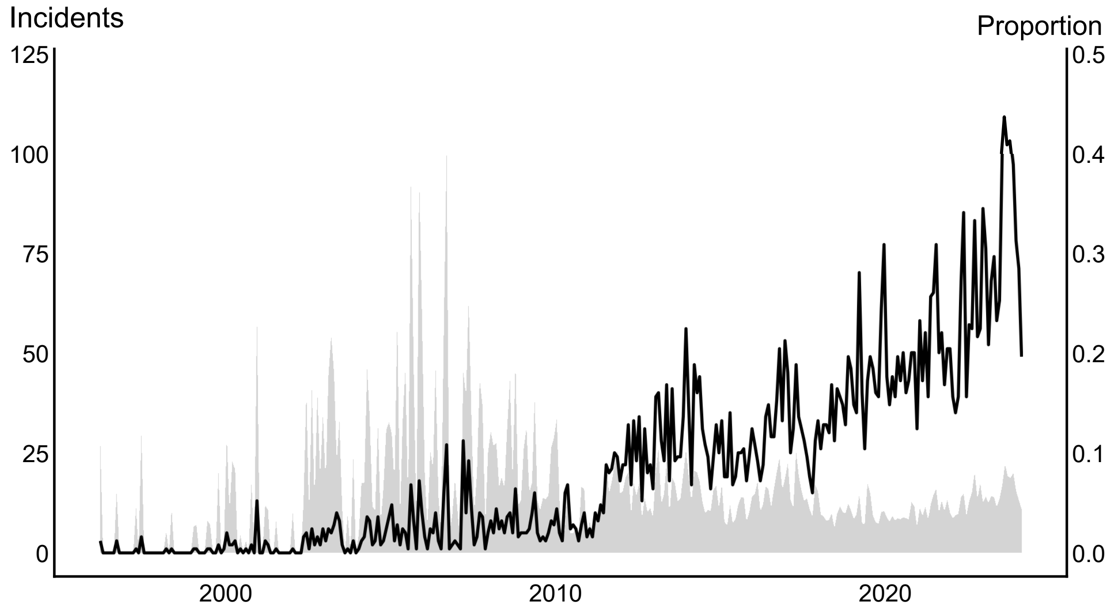

Figure B3: Conflict in Market Catchment Zones

Note: Incidents (solid line) include protests and riots, as recorded in ACLED (Raleigh et al., 2023). Proportion (shaded area) represents the share of incidents observed within market catchment zones in a given month relative to those observed across the entire continent during that same month.

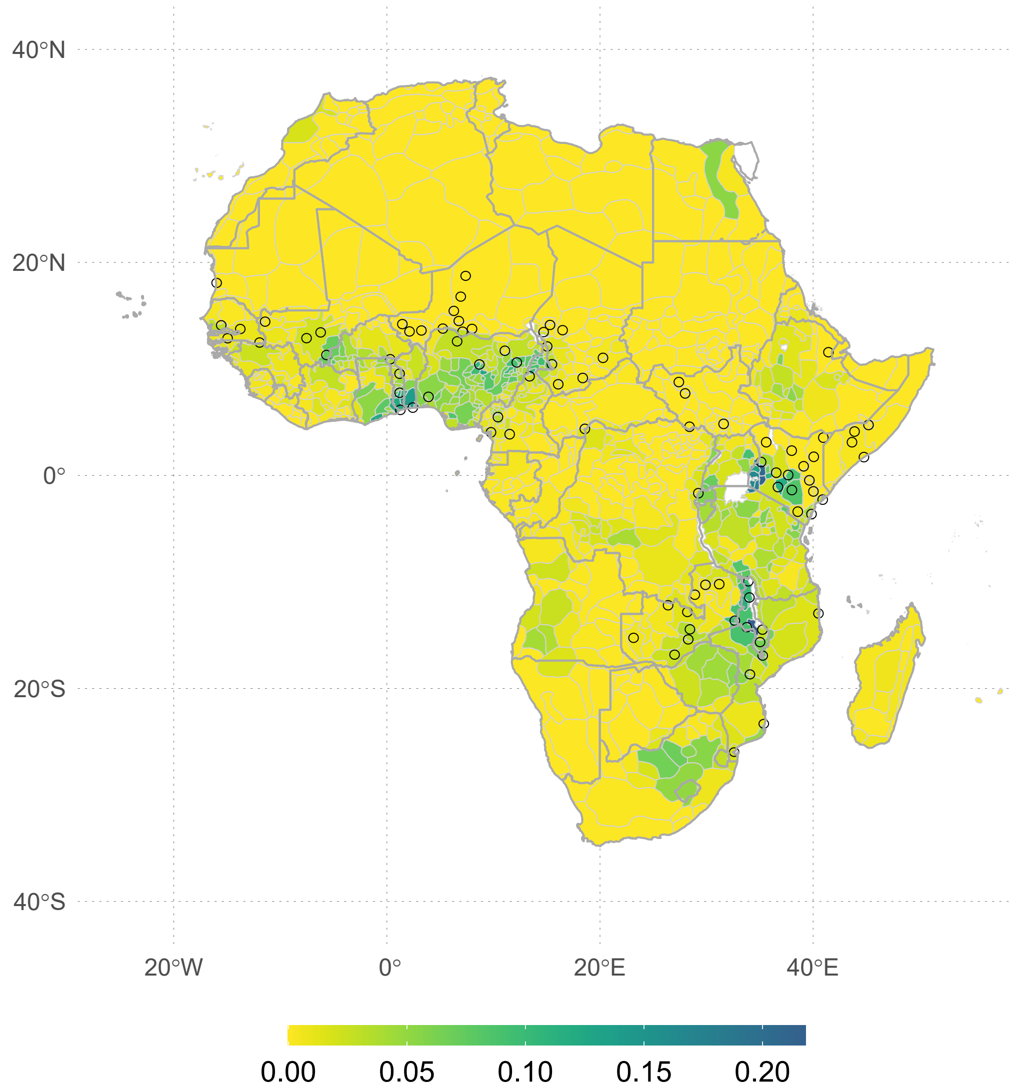

Figure B4: Proportion of Land Allocated to Maize Production Across Ethnic Groups

Note: Color-filled polygons depict the proportion of land allocated to maize production within ethnic boundaries. Gray circles identify market catchment zones. Data on ethnic boundaries are from the Murdock map (Murdock, 1959, 1967), and data on maize production are from IFPRI (2019).