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The Economic Origins of Conflict in Africa

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ABSTRACT

We study the impact of plausibly exogenous global food price shocks on local violence across the African continent. In food-producing areas, higher food prices reduce conflict over the control of territory (what we call "factor conflict") and increase conflict over the appropriation of surplus ("output conflict"). We argue that this difference arises because higher prices raise the opportunity cost of soldiering for producers, while simultaneously inducing net consumers to appropriate increasingly valuable surplus as their real wages fall. In regions without crop agriculture, higher food prices increase both factor conflict and output conflict, as poor consumers turn to soldiering and appropriation in order to maintain a minimum consumption target. We validate local-level findings on output conflict using geocoded survey data on interpersonal theft and violence against commercial farmers and traders. Ignoring the distinction between producer and consumer effects leads to attenuated estimates. Our findings help reconcile a growing but ambiguous literature on the economic roots of conflict.

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1 Introduction

Civil conflict is antithetical to development. In the second half of the twentieth century, 127 civil wars are estimated to have resulted in 16 million deaths, five times more than the death toll from interstate wars. Most of these wars have taken place in Africa, where conflict battles have killed between 750,000 and 1.1 million from 1989 to 2010. Indirectly, civil conflict has an enduring effect on disease, mortality, human capital, investment and state capacity.[1]

How might changing economic conditions shape the likelihood of conflict? This question is of demonstrable importance to policy, and it has spawned a large but inconclusive theoretical and empirical literature. From a theoretical perspective, economic shocks that alter the opportunity cost of violence could also affect the spoils of victory or a government's capacity to repel violence, yielding an unclear relationship between economic conditions and conflict. This ambiguity is reflected in a markedly inconclusive empirical literature, characterized by inconsistent findings and by significant identification challenges: income may affect conflict; conflict may affect income; and both may be influenced simultaneously by omitted factors, such as a the security of property rights.

We aim to overcome this ambiguity by exploiting two simple facts. First, agricultural products represent a higher average share of household production *and* consumption in Africa than in any other region. It follows that a plausibly exogenous change in world agricultural prices can generate opposing effects on real income across different households within a country. To wit, a spike in grain prices could increase income for grain producers while simultaneously reducing real income in net consuming households who lack access to cheap substitutes. Second, conflict itself can take observationally distinguishable forms. By increasing farm wages, for example, rising grain prices can reduce the supply of labor to armed groups, thereby causing a decline in conflict battles in rural areas. At the same time, high prices could provoke conflict over the appropriation of the commodity itself in the form of looting or "food riots". These distinctions—between producer and consumer effects and between types of conflict—allow us to derive and test a set of simple but clear predictions on the economic logic of violence that are difficult to explain with alternative mechanisms.

We first propose that a drop in agricultural commodity prices will raise the incidence of civil conflict battles in rural areas by reducing the opportunity cost of soldiering for farmers. A key assumption in this model is that the expected spoils of battle do not decrease at the same rate. We show that this is valid for conflict over the permanent control of territory, which is valued according to its discounted expected returns over a lifetime. If shocks are transitory, lower crop prices will increase the likelihood that rural groups engage in battles over territorial control. We call this type of battle *factor conflict*.

To test this prediction, we exploit panel data at the level of the 0.5 degree grid cell (around 55km

[1] See Ghobarah et al. (2003); Abadie and Gardeazabal (2003); Collier et al. (2003); Besley and Persson (2010). Statistics on civil war in the twentieth century are from Fearon and Laitin (2003); those on fatalities in Africa are calculated using the UCDP GED dataset (Sundberg and Melander, 2013). At least 315,000 of these fatalities were civilians.

$\times$ 55km at the equator) over the entire African continent. Data on factor conflict comes from the recently released UCDP GED dataset (Sundberg and Melander, 2013), which includes geocoded conflict events that (i) feature at least 1 fatality; and (ii) involve only organized armed groups that have fought in battles that directly caused at least 25 fatalities over the series from 1989 to 2010. To construct producer price indices, we combine high-resolution time-invariant spatial data on where specific crops are grown with annual international price data on multiple crops to form a cell-year measure. Controlling for both cell fixed effects and country-year fixed effects, we find that a within-cell standard deviation rise in producer prices lowers the probability of conflict by around 18% in food-producing areas.

We contrast this finding with an inverse effect in cells with no crop production. Through a negative effect on real income, we posit that food price spikes will cause those at the margin of a target level of consumption to engage in costly coping strategies. In the presence of factor conflict, this could imply recruitment to armed groups. Combining cross-sectional data on food consumption from the UN Food and Agriculture Organization (FAO) with temporal variation in world prices, we construct a consumer price index and find that higher values *increase* the duration of conflict in these food-consuming cells.

The upper panel of Figure 1 presents descriptive evidence of these results, using the simple FAO global food price index rather than the more detailed crop-specific indices we construct in the formal analysis. Separate nonparametric plots show that higher prices are associated with a reduction in factor conflict in cells where crops are produced (producer cells), and with an increase in factor conflict where they are not (consumer cells). This heterogeneity is not only important in its own right, but it also allows us to rule out as a unique explanation the most commonly posited alternative to the "opportunity cost" theory, namely that higher revenues from exports strengthen a state's capacity to repress or deter insurgent activities. That price fluctuations simultaneously raise and reduce factor conflict within states implies that household-level economic shocks play a large role in the decision to fight.

To further elucidate the role of economic conditions in conflict, we turn to a second simple fact: that conflict can take observationally different forms. We distinguish between two types: while *factor conflict* relates to the permanent control of territory, we define *output conflict* as a contest over the appropriation of surplus. This latter type of conflict is more transitory and less organized given that the goal is to take rather than to permanently displace, and we posit that higher prices will simultaneously increase the value of appropriable output and decrease the value of nominal wages for consumers in the short run. Thus, in contrast to the case of factor conflict, higher prices will *increase* output conflict in food-producing areas.

The lower panel of Figure 1 again presents initial descriptive support for this phenomenon. We measure output conflict using geocoded data on riots and violence against civilians from the Armed Conflict Location and Event Dataset (Raleigh et al., 2010), and see that rising global food prices are associated with a *higher* probability of output conflict in producer cells. We test this more formally in two empirical exercises below. In the first, we find that a one standard deviation increase in world food prices raises output conflict in food-producing cells by 15%. By contrast, for an equivalent change in the relevant world prices, no effect is detected in areas where production focuses on non-food crops ("cash crops"), as higher prices do not lower real wages for consumers. In the second exercise, we corroborate this finding using Afrobarometer survey data covering over 65,000 respondents in 19 countries over 13 biannual periods. We compile and geocode four rounds of pooled data and find that higher food prices increase the probability that commercial farmers report incidences of theft and violence in food-producing areas over the previous year. Moreover, we employ a triple difference framework and again find that the treatment effect is much larger in food-crop producing regions relative to cash-crop-producing regions.

Our study provides new evidence that individuals weigh the economic returns to violence against opportunity costs, with negative income shocks significantly and substantially increasing the risk of violent conflict events. Our findings challenge claims that the relationship between poverty and conflict is spurious (see Djankov and Reynal-Querol, 2010), as well as those stressing a unique explanatory role for "grievances" or expressive benefits that derive, for example, from repression or primordial ethnic hatreds.[2] To that end, we advance a literature originating in country-level studies that emphasize the robustness of correlations between conflict and economic factors. Collier and Hoeffler (2004) favor the opportunity cost explanation for conflict participation, whereas Fearon and Laitin (2003) argue that the relationship reflects instead the "state capacity" mechanism. Seminal work by Miguel et al. (2004) improves identification by using rainfall as an instrumental variable for GDP in a panel of African countries—an approach that no longer generates the same relationship with updated data (Miguel and Satyanath, 2011; Ciccone, 2011)—but does not distinguish between the mechanisms. Subsequent research further calls into question the validity of climate-derived instruments, given the many possible channels linking climate to conflict (Sarsons, 2015; Hsiang et al., 2013; Dell et al., 2014; Burke et al., 2015).

In part owing to concerns with the validity of climate instruments, a parallel literature instead exploits variation in global commodity prices to identify the impact of economic shocks on civil conflict. Results are notably inconclusive: Besley and Persson (2008) find that higher export prices increase violence through a *predation effect*, a result in line with a large literature linking oil prices in particular with conflict in low and middle income countries (Ross, 2015; Koubi et al., 2014; Collier and Hoeffler, 2005). Against this, Cotet and Tsui (2013) find no evidence of a significant relationship between oil discoveries and conflict, while Brückner and Ciccone (2010) find that higher export commodity prices *reduce* the outbreak of civil war, a result that Bazzi and Blattman (2014) find to be sensitive to updated data in a comprehensive attempt to reconcile sharply conflicting results in the cross-country literature. Analyzing a sample of all developing countries from 1957 to 2007, they find that higher prices reduce the duration of existing conflicts, and have no effect on

[2]See Gurr (1970) and Horowitz (1985) for influential theories of political and ethnic grievance motives for conflict respectively. We are careful to note that these schools of thought not strictly incompatible. Humphreys and Weinstein (2008) discuss the artificial nature of this dichotomy in analyzing correlates of conflict participation among survey respondent in Sierra Leone. They do, however, find evidence to suggest that economic motives offer a clearer explanation than grievance-based accounts.

the onset of new conflicts.

Recent advances in data quality have permitted a shift in focus from the country-level toward studies that exploit variation at the subnational level. For example, Berman and Couttenier (2015) and Fjelde (2015) suggest that export prices reduce the incidence of conflict battles in Africa. Focusing on Colombia, Dube and Vargas (2013) find that higher oil prices increase the likelihood of conflict events in oil-producing areas, while higher coffee prices have the opposite effect in coffee-producing areas—a result that corroborates Dal Bó and Dal Bó (2011), who posit heterogeneous effects of price shocks on conflict across capital- versus labor-intensive sectors. Harari and La Ferrara (2014) show that droughts in agricultural areas during critical growing periods increase the incidence of violent events in Africa.

Our analysis helps reconcile the current ambiguity in the literature. While the fundamental logic of our argument is similar to past studies—that variation in income shapes incentives towards violence—we show theoretically and empirically that a primary source of income variation used in the literature can affect different actors in different ways and can have differential effects on alternate forms of conflict. We show that failing to take these distinctions into account can lead to attenuated estimates of the impact of income variation on conflict. Furthermore, by identifying opposing effects within a state from the same price shock in a given period, our empirical strategy allows us to directly isolate the opportunity cost mechanism from the observationally similar state capacity mechanism—a longstanding problem in the literature. We do this using high-resolution data spanning the entire continent of Africa over a quarter century, combining georeferenced data on crop production locations, food prices, and data from three different conflict datasets. Our results provide comprehensive insight into the economic roots of conflict in Africa.

We proceed in Section 2 with our theoretical framework for the analysis. Section 3 introduces the data and provides a background on global food price variation. In Sections 4 and 5 we present our estimation strategy and results respectively. We interpret the magnitude of our results, evaluate the impact of projected future prices, and offer concluding remarks in Section 6.

2 Theoretical framework

In this section, we connect variation in food prices to the respective decisions of producers and consumers to engage in different types of conflict.

2.1 Producers

We begin our analysis by considering the impact of crop price changes on the decision of rural groups to harvest crops or to engage in *factor conflict*; that is, armed conflict over the control of agricultural land. We build initially on Chassang and Padro i Miquel (2009).

Consider two groups $i \in \{1, 2\}$ sharing territory of size N. Land is used to produce crops.

Group income in period t is generated according to:

$$Y_{it}(\mathbf{P_t}, \mathbf{N}_i, l_{it}) = [\mathbf{P_t} \cdot \mathbf{N}_i] l_{it},$$

where $\mathbf{N}_i = [N_{i1}, N_{i2} \ldots N_{in}]$ is the area of land that group i controls and N_{ij} is the share of $\mathbf{N}_i$ used to produce crop j; $\mathbf{P_t} = [P_{1t}, P_{2t} \ldots P_{nt}]$ is a vector of crop prices in period t; l_{it} is the amount of group i's labor used for production, and $\mathbf{P_t} \cdot \mathbf{N}_i = \sum_{j=1}^{n} P_{tj} N_{ij}$. Each group controls $\frac{1}{2}$ units of labor. If all labor is used for production, the total value of output in the economy is $Y_t = [\mathbf{P_t} \cdot \mathbf{N}]$. Groups seek to maximize the present discounted value of production, given by:

$$U_i = \sum_{t=1}^{\infty} \delta^t Y_{it},$$

where Y_{it} is group i income in period t and $\delta \in (0, 1)$ is a time discount factor.

In each period, world crop prices P_{jt} are drawn according to a lognormal cumulative distribution function $F(P_j)$, with support on $(0, \infty)$. Prices are generated by a stochastic process $\log P_{jt} = \mu_j + \phi \log P_{jt-1} + \epsilon_{jt}$, where the innovation term $\epsilon_{jt} \sim \mathcal{N}(0, \sigma^2)$ captures independent shocks to international market conditions. Total potential income $Y_t = \mathbf{P_t} \cdot \mathbf{N}$ can therefore vary exogenously over periods, while always remaining positive. We assume that $|\phi| < 1$, implying that shocks are not permanent.[3] The expected value of Y is therefore well defined as $\mathbb{E}(Y) = \bar{Y}$.

We assume that property rights are not perfectly protected—a reasonable assumption in many areas of rural Africa. Groups can therefore try to seize land by violent means as an alternative to productive activities. A first-mover advantage is obtained by launching such an attack, giving a group victory with probability $\pi > \frac{1}{2}$. In the case of conflict, both groups divert a combined share $v \in (0, 1]$ of labor from production to fighting. The aggregate opportunity cost of fighting is therefore vY_t.

Each group begins each period with the landholdings they controlled at the end of the previous period. If a transfer exists between groups that avoids conflict, it is implemented. If such a transfer does not exist, a war takes place. The winning group appropriates the land and the output of the losing group. The losing group receives a payoff of zero, and the game concludes.

More formally, the game proceeds as follows: (i) $\mathbf{P_t}$ is revealed and observed by both groups. (ii) Groups negotiate. If a transfer exists after which it is profitable for neither side to deviate unilaterally from peace, a settlement is reached and the game moves on to $t + 1$. (iii) If such a transfer does not exist, there is a decisive war after which the winner captures all output at t, and controls the entire territory N into the future. We show in Appendix Section A.2 that the set of parameters for which there exists a transfer that avoids conflict is the same set of parameters for which an equal distribution of land $\frac{N}{2}$ avoids conflict. We therefore proceed with the case in which each group controls $\frac{N}{2}$.

[3] We examine the empirical case for this assumption in Appendix Section A.1. We reject a unit root for 9 of 11 crops, consistent with recent findings in the literature (Wang and Tomek, 2007; Hart et al., 2015), suggesting that supply is elastic in the long run.

We begin by investigating a group's decision to attack after observing $\mathbf{P_t}$. If it decides not to attack, it receives the following expected payoff from peace:

$$\mathbf{P_t} \cdot \frac{\mathbf{N}}{2} + \delta V^P.$$

The first term is the return from peaceful farming on its landholding $\frac{\mathbf{N}}{2}$. The second term is the expected continuation value of future equilibrium play. The alternative option is to attack, which yields expected returns:

$$\pi\bigg((1-v)[\mathbf{P_t} \cdot \mathbf{N}] + \delta V^A\bigg).$$

With probability π, the attacker enjoys total production at period t less the aggregate opportunity cost of fighting, plus the continuation value of equilibrium play following victory. We can express the simple condition for peace as:

$$\mathbf{P_t} \cdot \frac{\mathbf{N}}{2} + \delta V^P > \pi\bigg((1-v)[\mathbf{P_t} \cdot \mathbf{N}] + \delta V^A\bigg).$$

Rearranging, peace is possible if:

$$\mathbf{P_t} \cdot \frac{\mathbf{N}}{2}(1 - 2\pi(1-v)) > \delta[\pi V^A - V^P]. \tag{1}$$

This condition generates important comparative statics for our analysis. It implies that sufficiently large negative price shocks will lead to war, provided the right hand side term is not negative. To check this, note that the highest value V^P can possibly take is:

$$V^P = \mathbb{E}\bigg[\sum_{t=1}^{\infty} \delta^t \mathbf{P_t} \cdot \frac{\mathbf{N}}{2}\bigg] = \frac{\bar{\mathbf{P}} \cdot \frac{\mathbf{N}}{2}}{(1-\delta)} \equiv \frac{\bar{Y}}{2(1-\delta)}, \tag{2}$$

the expected value of peacefully farming area $\frac{N}{2}$ into the future. As victory confers total control over all of N, it follows that:

$$V^A = \mathbb{E}\bigg[\sum_{t=1}^{\infty} \delta^t \mathbf{P_t} \cdot \mathbf{N}\bigg] = \frac{\bar{\mathbf{P}} \cdot \mathbf{N}}{(1-\delta)} \equiv \frac{\bar{Y}}{(1-\delta)},$$

the expected value of farming all of N for the foreseeable future.

These definitions imply that

$$\pi V^A - V^P \geq \pi \frac{\bar{Y}}{1-\delta} - \frac{\bar{Y}}{2(1-\delta)} = [2\pi - 1]\frac{\bar{Y}}{2(1-\delta)} > 0.$$

The right hand side of condition (1) is therefore positive for any V^P. Consider now the left hand side. Since $\mathbf{P_t}$ is always positive, a necessary condition for peace is

$$1 - 2\pi(1-v) > 0. \tag{3}$$

Note, however, that it is not a sufficient condition. As the right hand side of (1) is strictly positive, there must exist a $\mathbf{P_t}$ close enough to 0 such that conflict is inevitable, even if (3) holds. It follows that, irrespective of the equilibrium strategies that players expect to be implemented in future, conflict must occur for sufficiently bad economic shocks where a group's price vector $\mathbf{P_t}$ falls below some threshold $\tilde{\mathbf{P}}$.

Proposition 1. *There exists a vector $\tilde{\mathbf{P}} > 0$ such that rural groups will engage in factor conflict for realizations of $\mathbf{P_t} < \tilde{\mathbf{P}}$.*

Proof for the existence of $\tilde{\mathbf{P}}$ is presented in in Appendix Section A.3. The intuition is straightforward: a sufficiently low vector of prices will reduce a group's opportunity cost of violence by larger magnitude than it reduces the expected spoils of an attack. As factor conflict is concerned with the permanent control of land, a drop in current prices will have a comparatively weaker effect on the present value of victory.[4] This feature generates our prediction: higher realizations of $\mathbf{P_t}$ will reduce the probability of observing factor conflict events in a given agricultural area.

2.2 Consumers

We consider in this section the conditions under which price shocks lead net consumers to engage in two types of conflict. As alternatives to productive wage labor, consumers can instead directly appropriate producers' surplus (which translates to output conflict), or they can accept wages from armed groups (which leads to or exacerbates factor conflict). Commodity prices can determine a consumer's decision in three ways: (i) a *predation* effect, in which higher prices increase the value of appropriable surplus; (ii) an *income* effect, in which higher prices decrease real wages; and (iii) a combination of both.

To distinguish these mechanisms, we allow the vector of crop prices to contain three elements $\mathbf{P} = [P_f, P_c, P_m]$. The first element P_f is the price of what we call "food crops": crops that are both produced and consumed in a given cell. The second element P_c is the price of "cash crops": crops that are produced in a given cell but consumed elsewhere. The third element P_m is the price of "import crops": crops that are consumed in a given cell but produced elsewhere.

We continue with the environment introduced in Section 2.1. Aggregate labor is L, so that the total potential size of the economy in a given year is: $Y(\mathbf{P}, \mathbf{N}, L) = [\mathbf{P} \cdot \mathbf{N}]L$. Individuals provide either land or labor. Denote by r and w the respective rental prices, so that $Y = rN + wL$. The amount of land used to produce one unit of crop j is a_{jN}, and the amount of labor a_{jL}. In a

[4] This prediction is violated for the case where $\frac{d\bar{\mathbf{P}}}{d\mathbf{P_t}} \geq 1$, i.e. if prices follow a unit root process. This is because the expected payoff from fighting will covary sufficiently with the opportunity cost such that violence is rendered unprofitable. As noted above, we present evidence against this in Appendix Section A.1.

competitive equilibrium, farms earn zero profits:

$$ra_{jN} + wa_{jL} = P_j, \tag{4}$$

where P_j is the internationally determined price of one unit. Net consumers u maximize consumption. Indirect utility is therefore a function of prices and wages: $V_u(\mathbf{P}, w)$.

The first key addition to this environment is the existence of an appropriation sector for consumers: property rights are sufficiently weak to enable net consumers (or groups of net consumers) to appropriate surplus from landowners through the technology of output conflict. This can be chosen as an alternative to productive wage labor, as in Dal Bó and Dal Bó (2011). Denote by L_Q the share of labor in the appropriation sector, and by $Q(L_Q)$ the fraction of total output that is redistributed from the productive sector to the appropriation sector, where the function $Q(L_Q)$ is positive, continuous and strictly concave due to congestion effects, so that $Q(L) < 1$. The total amount of appropriated production is therefore $Q(L_Q)[\mathbf{P} \cdot \mathbf{N}](L - L_Q)$. A net consumer's decision to appropriate is one that satisfies the following condition:

$$\frac{Q(L_Q)[\mathbf{P} \cdot \mathbf{N}](L - L_Q)}{L_Q} > [1 - Q(L_Q)]w, \tag{5}$$

where the left hand side represents the individual payoff from appropriation, given by the value of appropriated goods per unit of labor allocated to that sector, and right hand side is the payoff from one of unit of productive work net of appropriation.

Net consumers will appropriate rather than work productively as long as it is profitable to do so. Denoting by $\mathbb{A}$ the left hand side of (5), and by $\mathbb{W}$ the right hand side, the equilibrium level of appropriation will be reached when $\mathbb{A} = \mathbb{W}$. Our goal is to determine how shocks to P_f, P_c, and P_m will affect this equilibrium. If $\frac{d\mathbb{A}}{dP_j} - \frac{d\mathbb{W}}{dP_j} > 0$, then the equilibrium level of output conflict $Q(L_Q)$ will increase.

In Appendix A.4, we derive how changes in prices for food crops, cash crops, and import crops affect conflict. We summarize these results here.

1. First, in food-producing cells, higher food prices P_f will increase the incidence of output conflict in the short run. The intuition is straightforward: higher food prices increase the value of output that accrues to landowners (generating a predation effect), while simultaneously decreasing the real wage of laborers in the short run (generating an income effect). This combination of effects increases the profitability of output conflict relative to productive wage labor (*Proposition 2*).

2. Second, the effect of cash-crop prices P_c on equilibrium output conflict is lower than the effect of food-crop prices P_f on equilibrium output conflict. This is because increases in P_c and P_f both increase the value of appropriable surplus, generating a predation effect, but only P_f will reduce real wages through an income effect (*Proposition 3*).

3. Finally, in consumer cells, higher imported food crops P_m will increase both output conflict

and factor conflict. In this case, P_m generates an income effect only. In keeping with a broad literature showing that poor households undertake costly or risky behaviors in response to income shocks that they cannot otherwise smooth (de Janvry et al., 2006; Dupas and Robinson, 2012; Miguel, 2005), this will increase the likelihood that poor consumers will (i) supply labor to local armed groups, which facilitates more factor conflict battles (*Observation 1*); and (ii) engage in output conflict, where output can be construed in a general sense as appropriable property of positive value (*Observation 2*).

2.3 Summary

Table 1 summarizes the main theoretical predictions.[5]

Table 1: Theoretical predictions

	Factor conflict	**Output conflict**
Food-producing cells	$\frac{dConflict}{dP_f} < 0$	$\frac{dConflict}{dP_f} > 0$
Food-consuming cells	$\frac{dConflict}{dP_m} > 0$	$\frac{dConflict}{dP_m} > 0$

In food-producing cells, higher food prices will reduce factor conflict, as rural groups choose to farm rather than to attack neighboring territory. At the same time, higher food prices will also *increase* output conflict, as net consumers appropriate increasingly valuable surplus while their real wages fall.

In food-consuming cells, higher prices reduce real wages. Consumers at the margin of a target consumption level are therefore more likely to accept a living wage from armed groups in conflict zones (which translates to more factor conflict); and to engage in interpersonal crime or looting (which translates to more output conflict).

3 Data and measurement

3.1 Structure

We construct a panel grid dataset to form the basis of our main empirical analysis, consisting of 10,229 arbitrarily drawn 0.5 X 0.5 decimal degree cells (around 55km × 55km at the equator) covering the continent of Africa. The unit of analysis is the cell-year. The cell resolution is presented graphically in Appendix Figure A1.

[5] We omit the distinction between food crops and cash crops for simplicity. We also do not consider the prospect of producers engaging in output conflict, as the opportunity cost of doing so is equal to the value of output that would be contested.

3.2 Conflict

Main factor conflict measure: *UCDP Factor Conflict* Theory dictates that the measure of factor conflict must capture large-scale conflict battles associated with the permanent control of territory, as distinct from transitory appropriation of food.[6] The Uppsala Conflict Data Program (UCDP hereafter) Georeferenced Event Dataset project is particularly suitable. It represents a spatially disaggregated edition of the well-known UCDP country-level conflict dataset used frequently in the literature. It records events involving "the use of armed force by an organised actor against another organised actor, or against civilians, resulting in at least 1 direct death" (Sundberg and Melander, 2013, pp.4). Moreover, it includes only dyads that have crossed a 25-death threshold in a single year of the 1989-2010 series.[7] The data are recorded from a combination of sources, including local and national media, agencies, NGOs and international organizations. A two-stage coding process is adopted, in which two coders use a separate set of procedures at different times to ensure that inconsistencies are reconciled and the data are reliable. Conflict events are coded for the most part with precision at the location-day level. We aggregate to the cell-year level, coding the variable as a one if any conflict event took place, and zero otherwise. This reduces the potential for measurement error to bias results, and is in line with the literature.[8]

Summary statistics for this measure of conflict incidence are presented in the top panel of Table 2. The unconditional probability of observing a factor conflict event in a cell-year is 2.7%, while the standard deviation is relatively large at 0.162. The row immediately beneath displays the corresponding *onset* statistics, defined as $\mathbb{I}(Conflict_{it} = 1 \mid Conflict_{it-1} = 0)$, where i is a cell. This sample contains all zeros plus onset years only. Conditional on peace at $t-1$, conflicts occur with probability of 1.4%. Beneath this again are $offset$ statistics, defined as $\mathbb{I}(Conflict_{it+1} = 0 \mid Conflict_{it} = 1)$. This is the equivalent of measuring the additive inverse of the persistence probability. Conditional on conflict in a given cell-year, the probability of peace the following year is 53.5%. Hence, this sample consists of all conflict years only. The sample average also indicates that time dependence is unlikely to be a first order concern in the analysis, given that a (thin) majority of conflict events are followed by peace. Nevertheless, we model onset and offset separately in the formal analysis, in part as a means of assuaging concerns of autocorrelation, and in part due to our theory. (In robustness tests, we also operate an alternative measure of factor conflict from the ACLED dataset; see Appendix B.2).

Main output conflict measure: *ACLED Output Conflict* Following our theory, the output conflict measure must capture violence over the appropriation of surplus. These events are likely

[6] In fact, this definition can be relaxed: our measure of factor conflict need only capture battles in which the contested resource is not food.

[7] For example, battles between the UNRF II and the Ugandan government crossed the 25-death threshold in 1997, therefore events in 1996 and 1998 in which deaths d were $0 < d < 25$ are also included.

[8] For each event, UCDP records the headline of the associated news article. Examples include: *"Five said killed, 250 houses torched in clashes over land in central DRC."* BBC Monitoring Africa, 9/21/2007; *"Tension runs high in west Ivory Coast cocoa belt. [20 killed.]"* Reuters, 11/14/2002; *"Tribes in Chad feud over land around well, 50 dead."* Reuters, 11/23/2000.

to be more transitory and less organized than large-scale factor conflict battles over the permanent control of territory. For this, the Armed Conflict Location and Event Data (ACLED) project provides an appropriate measure, covering the period 1997-2013. Like the UCDP project, ACLED records geocoded conflict events from a range of media and agency sources. Of eight conflict event categories included in the data, we discard all of the organized group "battle" categories and are left with two remaining forms of violence: "riots and protests" and "violence against civilians". We allow the output incidence measure to equal 1 if any of these two events occur in a cell-year, and 0 otherwise. Each classification includes unorganized violence by any form of group, including unnamed mobs. This definition captures incidences of food riots, farm raids and crop theft, as well as more general rioting and looting. No fatalities are necessary for events to be included in the data. Unconditional output conflict probability is 5%.[9]

Micro-level output conflict from Afrobarometer We turn to the Afrobarometer survey series for micro-level measures of interpersonal output violence. The first four rounds yield over 65,000 responses across 19 countries to questions on whether or not individuals experience theft or violence in the preceding year. In our formal analysis, we replace years with biannual time periods in order to increase our temporal variation. This produces 13 periods from 1999 to 2009. The data are collected as repeated cross-sections. In Table 2, we see that over 30% of respondents report having experienced theft in the past year, while 13% have been victims of violence.[10] In validation tests (discussed in Appendix Section C.4), we show that the ACLED output conflict variable is significantly correlated with both Afrobarometer survey measures, while the UCDP factor conflict variable is correlated with neither. The Afrobarometer dataset also permits us to investigate the first stage relationship between prices and poverty.

The upper panel of Figure 2 displays a time plot of the two main cell-level conflict event variables. On the vertical axis is the count of cells in which at least one conflict event occurs. *UCDP Factor Conflict* runs from 1989 to 2010, and *ACLED Output Conflict* runs from 1997 to 2013. Note that output conflict does not appear to vary with factor conflict, and is at no stage less frequent.

[9] ACLED data observations are accompanied by a brief note on the nature of each event. The output conflict events contain 3438 mentions of "riot-" (i.e., including "rioters", "rioting", and so on), or 0.39 for each time our output conflict incidence variable takes a value of 1; 1302 mentions of "raid-" (0.15); 1083 mentions of "loot-" (0.12); 1173 mentions of "thief", "thieve-", "theft", "steal-", "stole-", "crime", "criminal" or "bandit" (0.13); and 383 mentions of "food" (0.04). Examples of specific notes are: *"Around 25 MT of assorted food commodities to be distributed by a LNGO were looted from its storage facility in Bacad Weyne in the night of 31/07/2011."* (Somalia); *"A dozen armed men looted and pillaged food stocks in Boguila. After shooting their weapons in the air and attacking food stores, the bandits vanished within 45 minutes".* (Central African Republic)

[10] The respective questions are: *"Over the past year, how often (if ever) have you or anyone in your family: Had something stolen from your house?"* and *"Over the past year, how often (if ever) have you or anyone in your family: Been physically attacked?"*

3.3 Prices

To study the causal effect of price variation on conflict, we require price data with at least three general properties: variation over time; variation that is not endogenous to local conflict events and/or determined by local factors that might jointly affect prices and conflict; and variation that significantly affects real income at the household level in opposing directions across producers and consumers. Our approach is to construct local price series that combine plausibly exogenous temporal variation in global crop prices with local-level spatial variation in crop production and consumption patterns.

The middle and lower panels of Figure 2 present sets of global crop price series covering 1989 to 2013, our period of analysis. The prices are taken from the IMF *International Finance Statistics* series and the World Bank *Global Economic Monitor* (described in more detail in Appendix Section B.1). The top panel displays three important staple food crops for African consumers and producers: maize, wheat and rice, with prices in the year 2000 set to an index value of 100. Immediately apparent are sharp spikes in 1996 and, more notably, 2008 and 2011. Only wheat falls short of an index value of 300 in this period. In the lower panel, we present a selection of three non-staples ("cash crops" henceforth): coffee, cocoa and tobacco. These exhibit more heterogeneity, though coffee and cocoa prices reach high points toward the end of the series, before falling through 2012 and 2013. For both sets of crops, our study period captures historically important variation.

Variation in global crop prices is plausibly exogenous to local conflict events in Africa. As our sample consists of African countries only, we avoid serious concerns that cell-level conflict events directly affect world food prices—the entire continent of Africa accounts for only 5.9% of global cereal production over our sample period. Nevertheless, other factors could affect both simultaneously. The World Bank (2014) posits a range of likely explanations for food price spikes in 2008-09 and 2010-11. For instance, the surge in wheat prices is attributed to weather shocks in supplier countries like Australia and China, while the concurrent maize price shock is jointly explained by rising demand for ethanol biofuels and high fructose corn syrup, as well the effect of La Nina weather patterns on supply in Latin America. Although this set of correlates is broad, they are unlikely to influence our conflict measures through the same confluence of spatial and temporal variation as our price indices. For example, it is unlikely that a dry spell in Argentina could influence concurrently violence in rural and urban Uganda in opposing directions, other than through an effect on world food prices. Notwithstanding this, we variously control for country-year fixed effects, country time-trends, weather conditions, and oil prices in our formal analysis.

Finally, several studies evaluate large impacts of food price shocks on household welfare and consumption in developing countries. For example, Alem and Söderbom (2012) show that a 92% food price increase in Ethiopia between 2007 and 2008 significantly reduced consumption in poor urban households. Using survey data from 18 African countries in 2005 and 2008, Verpoorten et al. (2013) find that higher international food prices are simultaneously associated with lower and higher consumption in urban and rural households respectively. This resonates with our own analysis in the Appendix Section C.4, where we use Afrobarometer survey data to identify opposing effects of higher consumer and producer prices on self-reported poverty indices. Ivanic et al. (2012) focus on the 2010-11 spike, evaluating the effect of price changes for 38 commodities on extreme poverty in 28 countries. They find that the shock pulled 68 million net consumers below the World Bank poverty line of $1.25, while 24 million were pushed out of poverty through the producer mechanism.

Producer Price Index To compute producer prices, we combine temporal variation in world prices with rich high-resolution spatial variation in crop-specific agricultural land cover circa 2000. The spatial data come from the M3-Cropland project, described in detail by Ramankutty et al. (2008). The authors develop a global dataset of croplands by combining two different satellite-based datasets with detailed agricultural inventory data to train a land cover classification dataset. The method produces spatial detail at the 5 min level (around 10km at the equator), which we aggregate to our 0.5 degree cell level. Table 2 displays summary statistics on cropland coverage: 63% of cells contain cropland area larger than zero, while cropland as a share of the total area of the continent is 7.2%. Figure 3 presents crop-specific maps for a selection of six major commodities (maize, rice, wheat, sorghum, cocoa and coffee).

Our producer price index is the dot product of a vector of crop-specific cell area shares and the corresponding vector of global crop prices, with each crop weighted by the extent to which it is traded internationally by the country in which the cell falls. For cell i, country c and year t the price index is given by

$$PPI_{ict} = \sum_{j=1}^{n} (P_{jt} \times \underbrace{\frac{m_{jc} + x_{jc}}{y_{jc}}}_{trade\ weight} \times \underbrace{N_{jic}}_{crop\ land\ share}) \tag{6}$$

where crops $j \dots n$ are contained in a set of 11 major traded crops that feature in the M3-Cropland dataset and for which international prices exist. Trade weights are defined as the sum of imports and exports divided by total domestic production for a given crop, averaged over our entire sample period and Winsorized to form a time invariant weight varying from 0 to 1.[11] Inclusion of these weights ensures that our cell-specific index is not affected by variation in world prices of crops that are neither imported nor exported. Global crop-specific prices taken from the IMF *International Finance Statistics* series and the World Bank *Global Economic Monitor* and indexed at 100 in the year 2000.[12] In addition to this aggregated index, we also compute disaggregated variants that measure only food crop prices P_f (those which constitute more than 1% of calorie consumption in the entire sample) and cash crops P_c (the rest). The index varies over time only due to plausibly exogenous international price changes; all other components are fixed.

Consumer Price Index The consumer price index we construct is similar in structure to the producer price index, only the spatial variation instead comes from country-level data on food

[11] Trade and production statistics are taken from the FAO Statistics Division, accessible at http://faostat3.fao.org/home/E as at August 30th, 2015.

[12] Appendix Section B.1 presents the the descriptions and sources for the price data in more detail.

consumption from the FAO Food Balance Sheets. Food consumption is calculated as the calories per person per day available for human consumption for each primary commodity. It is obtained by combining statistics on imports, exports and production, and corrected for quantities fed to livestock and used for seed, and for estimated losses during storage and transportation. Processed foods are standardized to their primary commodity equivalent. Although the procedure is harmonized by the FAO, gaps in quality are still likely to emerge across countries and over time. Partly for this reason, we construct time-invariant consumption shares based on averages over the series 1985-2013.[13] These are similar to the crop shares N_{jic} above, only that crop shares in this instance represent calories consumed of crop j as a share of total calories consumed per person in a given country over the series.

Formally, the consumer price index in cell i, country c and year t is given by:

$$CPI_{ct} = \sum_{j=1}^{n} (P_{jt} \times \underbrace{\frac{m_{jc} + x_{jc}}{y_{jc}}}_{trade\ weight} \times \underbrace{\theta_{jc}}_{crop\ calorie\ share}) \tag{7}$$

where crops $j \ldots n$ are contained in a set of 18 crops that are consumed in Africa and for which world prices exist, making up 56% of calorie consumption in the sample, and containing important staples such as maize, wheat, rice and sorghum, as well as sugar and oil palm, which are used to process other foods. Again, temporal variation comes only from the price component.

3.4 Other data

In Table 2, *Urban area %* is share of each cell area that is classified as urban by the SEDAC project at Columbia University. The same source provides data on *Population* (estimated for the year 2000) and *Distance to city* (measured in 1000s of km).[14] *Luminosity* is a dummy variable indicating whether or not light density within cells is visible from satellite images taken at night during 2007 and 2008. These data are increasingly used as measures of subnational economic development, given the relative dearth of quality data in less developed regions, and in particular those affected by civil conflict (see Michalopoulos and Papaioannou, 2013, for a discussion on the particular suitability of nighttime lights as measure for economic development in Africa).[15]

Finally, Appendix Figure A2 plots the FAO Global Food Price Index (the most widely used index of its type) from 1990 to 2014. Spikes in 1996, 2008 and 2011 are consistent with the raw price data introduced above.

[13] Incorporating data from 1985 onwards allows for lags in the formal analysis.

[14] SEDAC datasets are downloadable at: http://sedac.ciesin.columbia.edu/data/sets/browse. Accessed August 10th, 2015.

[15] Under the assumption that luminosity measures economic development with a lag, we look to measure it at a relatively late stage in our series, being careful to avoid the period from 2010 onward due to the peaks in conflict observed in the ACLED dataset. We opt for a time invariant measure based on imagery from 2007 and 2008. The original data come from the Defense Meteorological Satellite Program's Operational Linescan System that reports images of the earth at night captured from 20:30 to 22:00 local time. We take our sample from Michalopoulos and Papaioannou (2013).

4 Estimation framework

The standard empirical approach to estimating the impact of income shocks on conflict takes some variation of the form:

$$conflict_{ct} = \alpha_c + \beta^n P_t + \gamma_c \times trend_t + \epsilon_{ct} \tag{8}$$

where the outcome is an indicator for conflict incidence in country c and year t; α_c captures country fixed effects, accounting for all time-invariant country characteristics that explain civil conflict; $\gamma_c \times trend_t$ is a country-specific linear time trend included to capture all time-varying factors that exhibit an analogous trend to conflict in country c; and ϵ_{ct} is the disturbance term, which is allowed to be serially correlated at the country level. The P_t term on the right hand side represents an exogenous income shock variable. In the case of food prices, that could take the form of the FAO world food price index, as in Hendrix and Haggard (2015) in their analysis of urban unrest, or could be a climate-related income shock, as in Miguel et al. (2004).

As noted above, this approach fails to account for potential opposing effects of prices on producers and consumers within a given country, likely leading to attenuated estimates of β^n. Furthermore, it makes it difficult to distinguish between the opportunity cost and state capacity mechanisms as structural explanations for any significant result. To overcome these barriers to inference, we instead require an empirical model that explicitly accounts for the opposing effects of world food prices on producers' and consumers' real wages.[16]

Factor conflict To study factor conflict, we propose a cell-level variant of equation (8), replacing the general price term with the producer and consumer price indices as follows:

$$factor\ conflict_{ict} = \alpha_i + \sum_{k=0}^{2} \beta^p_{t-k} PPI_{ict-k} + \sum_{k=0}^{2} \beta^c_{t-k} CPI_{ct-k} + \gamma_c \times trend_t + \epsilon_{ict} \tag{9}$$

where the outcome is factor conflict in cell i measured as incidence, onset or offset binary variables; α_i represents cell fixed effects; PPI is the producer price index; CPI is the consumer price index; the fourth term is the country-specific time trend; and the final term is the error, which we cluster along two dimensions to allow for serial correlation at the cell-level and spatial correlation across cells within a country.[17] We sum price effects over three years to account for delayed effects of past shocks, or potentially for displacement effects where shock hasten conflict that would have happened anyway.[18] We estimate the specification with both a linear probability model (LPM) as well as conditional logit, preferring LPM for the main analysis as it allows for more flexible specifications and a clear interpretation of the coefficients; results are qualitatively similar either way. In line with our theoretical predictions, when the outcome is factor conflict incidence or onset we expect that β^p will be negative, and β^c will be positive. When the outcome is factor conflict

[16] We explore the quantitative implications of this "naive" approach in Section 5.4 below.

[17] We also present results where the error term is allowed to be spatially and serially correlated in groups of contiguous cells, following Conley (1999)

[18] Results are not sensitive to the choice of $k = \{0, 1, 2\}$.

offset, we expect the opposite.

The identifying assumption in Equation 9 is that, after accounting for time-invariant factors at the cell level and common trending factors at the country level, variation in consumer and producer prices are not correlated with other unobserved factors that also affect conflict. One potential concern is that unobserved shocks that are not picked up by the country trends could be correlated with both crop prices and conflict. To account for this, we control for some of these potential confounds (such as local weather and oil price indices) in robustness tests, and we also estimate an alternate form of Equation 9 that includes country-year fixed effects γ_{ct}:

$$factor\ conflict_{ict} = \alpha_i + \sum_{k=0}^{2} \beta^p_{t-k} PPI_{ict-k} + \gamma_{ct} + \epsilon_{ict} \tag{10}$$

Here, β^p is estimated off within-country-year variation in prices and conflict, eliminating concern about common time shocks. The cost to this approach is that we can no longer include consumer prices, as these do not vary within-country in a given year.[19]

Output conflict For output conflict, our theory predicts (i) that rising food prices will *increase* incidence in food-producing cells, in contrast to case of factor conflict; (ii) that this effect will be larger for food crop price shocks than for cash crop price shocks; and (iii) that increases in the prices of imported food crops will lead to more output conflict. We test these predictions with the following specifications:

$$\begin{aligned} output\ conflict_{ict} = \alpha_{oi} &+ \sum_{k=0}^{2} \beta^{pf}_{t-k} PPI^{food}_{ict-k} + \sum_{k=0}^{2} \beta^{pc}_{t-k} PPI^{cash}_{ict-k} \\ &+ \sum_{k=0}^{2} \beta^{m}_{t-k} CPI_{ct-k} + \gamma_c \times trend_t + e_{ict} \end{aligned} \tag{11}$$

and

$$output\ conflict_{ict} = \alpha_{oi} + \sum_{k=0}^{2} \beta^{pf}_{t-k} PPI^{food}_{ict-k} + \sum_{k=0}^{2} \beta^{pc}_{t-k} PPI^{cash}_{ict-k} + \gamma_{ct} + e_{ict}, \tag{12}$$

where PPI^{food} is a component of the producer price index that contains information only on food commodities that constitute more than 1% of total average consumption in our sample (capturing P_f from the theoretical model). These include the major staples of maize, wheat, rice and sorghum. The PPI^{cash} component picks up the remaining cash crops such as coffee, tea and tobacco (capturing P_c from the model). Equation (11) includes the consumer index CPI to capture the impact of prices net of the production effects (P_m in the model). Equation (12) includes country-year fixed effects, leaving only the two subnational producer price indices. According to the model, β^{pf} and

[19] In later specifications, we use our theory to introduce heterogeneity across cells that permits the inclusion of both the consumer price index and country-year fixed effects.

β^m will be positive, and $\beta^{pf} > \beta^{pc}$.[20]

5 Results

5.1 Factor conflict

Main results In all regressions, price indices are measured in terms of the average within-cell (i.e., temporal) standard deviation. Panel A in Table 3 presents results from regressions that omit the consumer price index and include country × year fixed effects. The producer price index used in column (1) omits trade weights, and the sample therefore includes cells from countries that do not feature in the FAO dataset. Column (2) includes trade weights in the index. These specifications are repeated for conflict onset and offset in the following columns in order to decompose the conflict incidence effects in (1) and (2). In both incidence specifications, higher producer prices significantly reduce the risk of factor conflict. The magnitudes are large: a one (within-cell) standard deviation rise in producer prices lowers the probability of factor conflict by 15.4% of the mean without trade weights, and by 17.7% of the mean with trade weights. Both estimates are significant at the 1% level with Conley standard errors. When errors are (two-way) clustered, the trade-weight estimate is significant at the 5% level and the without-trade-weight estimate is significant at the 1% level. Both estimates are driven jointly by a lower onset risk and by a higher offset probability (i.e. a reduction in conflict duration).

Panel B in Table 3 presents the main results that include the consumer price index. Three facts are particularly noteworthy. First, higher consumer prices significantly increase the duration of factor conflict. A standard deviation rise in prices reduces the probability of a conflict ceasing by 16.5% and 13.7% with and without trade weights respectively, but the effect on conflict onset is not significant.[21] This is consistent with the idea that rising prices force low-income net consumers to join existing armed groups rather than launch new conflicts. Second, the magnitude of the producer effects is larger across the board than in Panel A. This is consistent with the idea that the latter estimates are biased downward due to omitted variable bias. Third, producer and consumer price effects are significantly different from each other in all six specifications. This is consistent with our main model prediction on factor conflict.

In Appendix Section C.1, we explore rthe obustness of these main results to the inclusion of weather and oil price controls, to alternate ACLED-based measures of territorial change, to different levels of aggregation, to explicitly modeling spatial spillovers, and to a conditional logit rather than a linear probability model estimator. Our main results are robust to all of these variants.

The upper panel of Figure 4 presents visual output based on a variant of the specification estimated in column (1). The regression includes quadratic fits of the producer and the consumer price indices (without lags), as well as cell fixed effects and country-year time trends. The figure

[20]The predictions are with respect to conflict incidence and onset; the opposite sign is predicted when conflict offset is the outcome variable.

[21]Unless otherwise stated, results presented hereafter are based on models with trade weights in the price indices.

support a linear treatment of the main effects.

Heterogeneity Our model also provides guidance on a source of heterogeneity in the consumer price effect that we can test in the data. We outline conditions necessary for high food prices to cause net consumers to join armed conflict groups: they must have few assets for dissaving; they must have no access to credit or insurance; and they must be earning a lower wage than that offered by the armed conflict group. In short, we should not expect to find the same impact of consumer prices on factor conflict in more economically developed cells, all else equal.

Following a now-voluminous literature, we proxy local economic development by using satellite-based measures of luminosity at night, coding a luminosity variable equal to unity if a grid cell showed non-zero luminosity in 2007-08. The impact of the consumer price index on factor conflict is therefore predicted to be lower in cells where $luminosity = 1$. It is conceivable also that in the event of negative price shocks, farmers who are proximate to local non-agricultural labor markets will be less likely to join armed groups than those who do not. If we assume that lit cells are more likely than dark cells to contain employment opportunities outside of the agricultural sector (all else equal), then the impact of the producer price index on factor conflict also ought to be closer to zero where $luminosity = 1$.

Introducing the luminosity variable allows us to estimate a variant of equation 10 that contains $CPI_{ct-k} \times luminosity_{ic}$, $PPI_{ict-k} \times luminosity_{ic}$ and country × year fixed effects, as the interaction generates variation in the consumer price index at the subnational level. To that end, this exercise serves as both a robustness exercise as well as a test of theoretical implications.

We are cautious of several factors that may impede our interpretation of these interaction effects. First, the interaction variable might simply capture the fact that lit cells are likely to contain larger populations, which is necessary for conflict to occur in the first place. We thus control for cell-year level CPI and $PPI \times population$ interactions in all specifications.[22] Second, global price pass-through is likely to be larger in lit cells than in dark ones, even controlling for population, as economic development may reflect more trade openness. This would bias the effect of the luminosity interaction terms towards zero, as we are predicting that economic development mutes the effect of prices on violence (while the passthrough story implies the opposite). We attempt to capture this by creating a proxy for market remoteness, measured by the distance in 1000kms to the (next) nearest lit cell. Third, the luminosity variable is correlated with other factors that might be associated with conflict through alternative mechanisms. We consider three: distance to capital city, which captures the possibility that state counterinsurgency capacity is weaker the farther one is from the capital; mountain terrain, with may facilitate insurgency; and the sophistication of precolonial governance in the ethnic homeland containing a given cell, measured by Murdock (1957) as the degree of political centralization, and found by Michalopoulos and Papaioannou (2013) to

[22] We compute the cell-level population variable using data from the Socioeconomic Data and Applications Center (SEDAC) project at Columbia University. Datasets are downloadable at: http://sedac.ciesin.columbia.edu/data/sets/browse.

be correlated strongly with contemporary economic development.[23]

The results of this test are presented in Table 4. Column (1) features a model with country time trends, cell fixed effects, and prices $\times$ population as controls; in column (2) we add country $\times$ year fixed effects; and in column (3) we add the rich battery of controls described above. Conflict incidence is the dependent variable In all three specifications. The main finding is that, in specifications with country $\times$ year fixed effects, a one standard deviation rise in consumer prices significantly increases factor conflict in dark cells by 19-20% compared to more economically developed lit cells. We also note substantial heterogeneity in the impact of the PPI—from -48% in dark cells to -20.8% in lit cells in column (3)—but these estimates are narrowly outside of conventional levels of statistical significance.

Taken together, this exercise supports an implication of theoretical model: that the effect of consumer price shocks on factor conflict is weaker in more economically developed areas. We also find suggestive evidence that lower producer prices are less likely to spark conflict when farmers have recourse to proximate non-agricultural labor markets. Both forms of heterogeneity are proxied by nighttime luminosity from satellite images. This finding suggests that is it not only economic shocks that relate to conflict, but also the interaction of shocks and levels.

5.2 Output conflict: ACLED

Main results In Table 5, we present the impact of the aggregated PPI and the CPI on output conflict to allow for a comparison with the factor conflict results. Columns (1) and (2) display results from specifications with country $\times$ year fixed effects (CYFE) and without the CPI. In contrast to the case of factor conflict, we see that a one standard deviation rise in producer prices leads to an *increase* in the probability of output conflict of 14.4% and 15.1% with and without trade weights respectively. In (3) and (4), the impact of the CPI is 14.4% and 8.0%. All estimates are significant at the 1% level.

The lower panel of Figure 4 presents visual results from a regression of output conflict on the producer price index, the consumer price index (both quadratic fits), a country time trend and cell fixed effects. In contrast to the upper panel, the producer price effect slopes upward. Taken together, the two panels corroborate the predictions outlined in Table 1.

Table 6 and Appendix Table A8 present results from the specifications described in Section 4, in which the producer price index is separated into food crops (*Producer Price Index: Food Crops*) and cash crops (*Producer Price Index: Cash Crops*). Six models are featured: one without trade weights and one with trade weights for each of the output conflict incidence, onset and onset outcome. Higher food prices lead to a significant and economically large increase in output conflict incidence and onset, whether with Conley standard errors or with errors clustered by cell and by country-year. Focusing on column (2) in Table 6, a standard deviation increase in food prices raises the probability of output conflict incidence by 16.6%. By contrast, cash crop prices have no clear

[23] Data on distance to capital city and mountain terrain are taken from the PRIO GRID dataset; data on pre-colonial political centralization is taken from Michalopoulos and Papaioannou (2013).

impact. Consistent with our predictions, both effects are significantly different from each other at the 1% level in all incidence and onset regressions, although this is not the case in the offset regressions, where both effect are close to zero. Again in line with our theory, the consumer price index also enters with a large and significant coefficient: a standard deviation rise leads to a 7.9% increase in output conflict incidence, and analogous results are shown for onset and offset.

In Appendix Table A8, we omit the consumer price index and include country $\times$ year fixed effects, finding similar results.[24] As in case of factor conflict above, we test for robustness to the inclusion of potential weather and oil confounds, to higher levels of aggregation, and to alternate estimators, and find our results quantitatively and qualitatively robust in each case (see Appendix C.2).

We also explore whether our measure of output conflict is just picking up "food riots" that may be driven as much by a desire to provoke government policy changes than by a desire to directly appropriate property from others (Bellemare, 2015). This interpretation is supported by Hendrix and Haggard (2015) and Bates and Carter (2012), who find that governments frequently alter policies in favor of consumers in the wake of price shocks. Food riots in this context will occur in urban centers where government authorities can be expected plausibly to respond, and we therefore interact our consumer price index with two different measures of urbanization in order to detect whether results are differentially driven by urban unrest.

Results are shown in Table A13 and described in more detail in Appendix C.2. Using either an area-based or population-based definition of whether a cell is "urban", we find that the effect of higher CPI on output conflict remains positive and significant in non-urban areas. The effect in urban areas is larger than the rural effect using the area-based measure, but is indistinguishable using the population-based measure. We conclude that our main output conflict results are not driven by urban food riots or protests designed to create unrest and agitate for policy reforms.

We also investigate whether the contrasting impact of producer food crop prices on both outcomes can be fully explained by the different sample periods or data collection projects. Results suggest that this is not the case, with findings qualitatively unchanged on the sample restricted to the same set of years (see Appendix Table A14).

5.3 Output conflict: Afrobarometer

In this section, we incorporate data on interpersonal conflict from multiple rounds of the Afrobarometer household survey project. Merging our high resolution panel grid with Afrobarometer permits an alternative strategy to investigate the relationship between food prices and output conflict, as well as a direct way to assess the assumed "first stage" relationship between food price movements and income movements, as assumed in our theory. We describe how we process and merge the Afrobarometer data in Appendix Section C.4.

In Table A15, we examine the effect of the producer and consumer price indices on three different

[24]The results in Appendix Table A8 also show that Conley standard errors are smaller than two-way clustered errors, which are presented in the main text.

self-reported poverty measures, controlling for survey round fixed effects, country fixed effects, a country-specific time trend, the age of the respondent, age squared, education level, gender, urban or rural primary sampling unit, and a vector of 0.5 degree cell-level crop-specific land area shares, so that the producer price index is not picking up time-invariant features of agricultural production. We find that a one standard deviation increase in the CPI raises the probability that a respondent is above the median poverty index value by 12.2%, or from 45% to 50.5% at the mean. We see that an equivalent change in the PPI has a negligible effect on the overall poverty index using the full sample, but that higher producer prices are associated with lower self-reported poverty for respondents who report farming as their primary source of income. These results are broadly consistent with the assumptions of our theory: higher food prices represent negative income shocks for consumers, and positive shocks for producers.

We also confirm that our Afrobarometer measures of interpersonal conflict—which include whether individuals over the previous year report (i) having been victims of theft; (ii) having been victims of physical assault; (iii) or having partaken in "protest marches" (which includes demonstrations, riots or looting)—are more likely picking up output conflict rather than factor conflict. We regress each binary indictor on our cell-level *ACLED Output Conflict* variable in three specifications: one bivariate, one with survey round fixed effects and country fixed effects, and one that adds the *UCDP Factor Conflict* measure in order to determine if the survey measures are also (or instead) capturing factor conflict. In eight of the nine specifications, the survey measures correlate significantly with *ACLED Output Conflict Variable*. The exception is the bivariate protest variable regression. The *UCDP Factor Conflict* variable does not enter significantly in any specification.

Food prices and output conflict in Afrobarometer Proposition 2 implies that higher food prices will cause net consumers to appropriate output in food-producing areas. From whom do they appropriate? In the model, we imply that output violence is perpetrated against landowners. In the data, we can approximate this by identifying *commercial* farmers, who number 6,751 (11%) of the 59,871 respondents to the question on occupation. Moreover, we can also include traders (7%) as potential victims of output violence, relaxing the assumption that output is traded only by producers at the farm gate. We focus specifically on the theft and violence outcomes, as they most directly correspond to the theoretical concept of output violence.

The main disadvantage of the micro-level Afrobarometer data is that we do not observe the same farmers in different periods, meaning we cannot control for individual unit fixed effects as in the cell-level analysis. This raises the possibility that unobserved individual factors may explain why commercial farmers respond differently to price shocks than do other survey respondents. To overcome this problem, we compare whether the impact of higher prices on reported conflict among farmers/traders is higher in food-producing cells than in cash-crop-producing cells. According to our model, output conflict rises in the PPI for food crops because the value of appropriable output increases while real wages *simultaneously decline*. By contrast, the PPI for cash crops will raise the value of appropriable output *without* causing a simultaneous decline in real wages. We can estimate the difference in these effects with a framework similar in concept to a triple difference approach.

Two specifications are estimated for each of the theft and violence outcomes. In the first, we control for country fixed effects and for crop-specific cell area shares in order to account for fixed differences between areas that grow different crops.[25] We also control for occupation, and for the set of controls listed in the previous subsection, including a country-specific time trend and fixed effects for countries and survey rounds. In the second specification, we control for cell fixed effects—therefore holding all cell-level time-invariant characteristics fixed—as well as country × period fixed effects and the individual controls. That allows us to compare only the effect of price changes on farmers/traders between food-producing cells and cash crop producing cells within countries.

Table 7 shows our main results. In column (1), we present the country fixed effects model with theft as the outcome. We first note that traders are significantly more likely than other respondents to be victims of theft when food prices rise in food-producing cells. By contrast, farmers and traders are both *less* likely to be victims of theft when cash crop prices rise in cash-crop-producing cells. Finally, the consumer price index also enters with a positive (but noisy) coefficient, indicating that food prices increase theft across the full sample (i.e., in cells where food is imported). The second panel presents treatment effects, standard errors and the associated p-values for the impact of food crop prices compared to cash crop prices on both farmers and traders. We see that the impact of the food crop PPI relative to the cash crop PPI on theft against both farmers and traders is large and significant. Standard effects can be derived from the third panel: food crop farmers are 14.3% more likely than cash crop farmers to be victims of theft following a standard deviation rise in respective commodity prices in terms of the dependent variable mean (p-value = 0.006). The equivalent effect for traders is 15.1% (p-value = 0.017). In column (2) we add cell fixed effects and country × period fixed effects. The food price treatment effect is now 16.2% for farmers (p-value = 0.005) and 13.5% for traders (p-value = 0.021). Again, both farmers and traders are less likely to be victims of theft when cash crop prices rise, and are more likely to be victims when food crop prices rise.

In columns (3) and (4), we present evidence for an analogous effect on violence. While theft is targeted against both farmers and traders in food-producing cells, violence is directed exclusively at farmers. Focusing on column (3), commercial food crop farmers are 19.1% more likely than cash crop farmers to be victims of physical assault following a standard deviation rise in prices. The p-value for the treatment effect is 0.007. Adding cell fixed effects and country × period fixed effects in column (4) makes little difference (16.2%, p-value = 0.01). The consumer price index estimate is again not significant.

While remarkable in their own right, these results provide robust support for our theoretical account of output conflict. Higher food prices in food-crop cells substantially increase the likelihood that commercial farmers will experience theft and violence relative to equivalent changes to cash crop prices in cash-crop cells. We attribute this effect to the role of food prices as an income deflator

[25] For example, less remote cells may grow more cash crops for export.

for net-consumers, owing fundamentally to the relative price-inelasticity of demand for food.

5.4 Naïve estimates

In our main analysis we make critical distinctions between what can be broadly defined as consumer effects and producer effects of crop prices on violence. We implement this empirically in two ways: (i) harnessing cell-level data to separate the impacts of producer prices and consumer prices; and (ii) separating factor conflict from output conflict.

In this section, we explore the ramifications of ignoring these differential effects by instead using the country-level data and catch-all conflict and price measures commonly used in prior literature.[26] We first present results from the naïve specification (8), where the outcome variable alternates between the (country-level) incidence of UCDP conflict and the combined categories of the ACLED conflict events, and the price variable alternates between the aggregated producer and consumer price indices. This reflects a common approach taken to estimate the impact of producer and consumer price shocks on country-level conflict respectively.

As shown in the first column of Panels A and B in Table 8, none of the estimated effects on UCDP conflict are distinguishable from zero at standard confidence levels. The null effects are due jointly to attenuation bias caused by the omission of the "opposing" price variable, and partly by the reduction in efficiency caused by the country-level aggregation of the conflict dummy variables. In Panel C we include both price variables in order to quantify these two sources of error. For example, the PPI impact on UCDP conflict in the full cell-level specification is -17.2% (p=0.001); in the naive regression it is -1.1% (p=0.795).

In the second column, we replace the outcome variable with the ACLED measure that captures all categories of recorded conflict events, as in Harari and La Ferrara (2014). Both coefficients are again indistinguishable from zero. Were any of them significantly larger than zero, we would not be able to distinguish between three competing mechanisms: the consumer price impact on factor conflict, the consumer price impact on output conflict, or the producer price impact on output conflict—in effect, any combination of the three cells in Table 1 that predict a positive sign. Including both indices simultaneously does not resolve the ambiguity.

We conclude that failing to account for important distinctions between producer and consumer prices, between factor and output conflict, and between country- and cell-level analysis leads to a muddled account of the relationship between world food prices and conflict in Africa.

6 Discussion and conclusion

6.1 Magnitudes and projections

We illustrate the magnitude of our main estimates in two exercises. First, we offer back-of-the-envelope estimates of the impact of a change in crop prices identical to that which occurred between

[26]We note that Bazzi and Blattman (2014) control for a country-specific consumption index in their country-level analysis of export prices and conflict.

2004 and 2008. The consumer price impact on factor conflict incidence is +16.4% in terms of the sample mean, while the producer effect is −16.6%. This implies that in consumer cells with no production, the risk of factor conflict increased substantially over the period due to the observed price increases, while effects roughly netted out for cells with both production and consumption. Given that 63% of cells report non-zero production, we estimate an Africa-wide average effect of the 2004-08 food price increase on factor conflict of $+16.4 - 16.6(0.633) = +5.89\%$. For output conflict, we estimate an average consumer price impact of +27.4% across all cells from the food price increase (through the income effect), and a producer price impact of +19.6% in producer cells (through the predation effect), giving a weighted average impact of around +40%.

In the second exercise, we apply leading projections of future grain prices to our estimates. The International Food Policy Research Institute (IFPRI) (Nelson et al., 2010) presents a range of scenarios for maize, rice and wheat prices in 2050. All three are projected to rise across all scenarios, due largely to continued global economic and population growth on the demand side, and to the effects of climate change on the supply side. The baseline scenario in the absence of climate change is based on income projections from the World Bank and population projections from the UN. We interpret the projected impact of climate change on supply as the mean of four scenarios outlined in the original analysis. We estimate the impact of these price movements on factor conflict and output conflict through both the producer price effect and the consumer price effect. For all four estimates, we present a "perfect climate mitigation" scenario in which all greenhouse gas emissions cease in 2000 and the climate momentum in the system is halted, in addition to the mean climate change scenario.

The projections are displayed in Figure 5. Each projection begins in 2010 with the probability of conflict normalized to 100. The 2010 unconditional probability is 2.15% for factor conflict, and 4.9% for output conflict. In the upper panel, we show that the change in grain prices from 2010-2050 will generate a producer price effect on factor conflict of around −28% with climate change, and −14% without. At the same time, higher prices will generate a consumer price effect on factor conflict of +30% (+15%). In all cells but those with above-average levels of food production, prices in 2050 will lead to a higher probability of large-scale factor conflict events. The weighted average effect is +12%, about half of which can be explained by climate change.

The lower panel presents the projected impact of 2050 prices on output conflict. The producer price effect is +27% with climate change, and +14% without. The consumer price effect is +42% (+17%). This implies a weighted average effect of +59%, around two-thirds of which is explained by climate change.

It is important to acknowledge the limitations of this partial equilibrium exercise. We do not model the direct impact of changes to global population, income and climate on conflict; rather, we model their indirect impacts through prices using parameters estimated in our 1989-2013 sample. Nevertheless, the exercise suggests that future prices will lead to more political instability in the form of factor conflict (particularly in consumer areas), and to more predation in the form of output conflict (particularly in producer areas). Mitigating entirely the effect of climate change would mute over half of the overall effect.

6.2 Concluding remarks

We draw a number of conclusions on the economic origins of violence in Africa. First, we identify a large causal effect of income shocks on civil conflict. Consistent with emerging research on subnational conflict events from Harari and La Ferrara (2014), Berman and Couttenier (2015) and Dube and Vargas (2013), our results help to resolve ambiguity in the large body of existing country-level studies. Moreover, in identifying opposing effects of prices on the behavior of consumers and producers within countries, we offer one explanation for attenuated estimates in this literature.

Second, we advance knowledge on causal mechanisms. We exploit exogenous variation in world prices that generates opposing subnational income shocks. The corresponding impacts on violence are inconsistent with one common explanation for the inverse country-level correlation between income and civil conflict, in which GDP is considered an approximation of a state's capacity to deter or repress insurgency. Our results point instead to an important role for individual income and substitution effects. Civil conflict in Africa responds to changes in household-level economic payoffs and opportunity costs.

Third, we formalize theoretical and empirical distinctions between different forms of conflict. In food-producing cells, higher prices reduce the incidence of "factor conflict" over the permanent control of territory. This, we argue, is because rural groups profit from harvesting crops rather than launching attacks. Conversely, higher prices *raise* the incidence of "output conflict" over the appropriation of surplus. This is because higher food prices raise the value of appropriable surplus while simultaneously lowering real wages for net consumers. In cells where food-crops are only consumed, higher prices increase both forms of conflict. Our results suggest that future research on the economic roots of conflict should distinguish between varieties of conflict, as the failure to do so could lead to further attenuation.

Fourth, we highlight the importance of a spatially disaggregated approach to the economics of civil conflict. Our cell-level data permit tests of theoretical predictions for which country-level data are not suitable. We also disaggregate further to the individual level in order to validate our cell-level results, finding firstly that food price shocks have opposing effects on poverty for farmers and consumers; and, second, that food price shocks increase self-reported theft and violence perpetrated against commercial farmers relative to equivalent changes in cash crop prices.

We interpret our results with caution. The confirmation that economic shocks shape civil conflict by no means precludes a significant causal role for political or social grievances. Indeed, it is difficult to imagine that civil conflict is not partly driven by non-economic factors. Nevertheless, we do reject claims that the link between income and conflict is unimportant or spurious. Similarly, our findings do not rule out the potential importance of the state counterinsurgency capacity mechanism in other contexts.

Finally, we note potentially important policy implications of our results. Our sample covers an entire continent over several years, assuaging serious concerns about external validity. Moreover, our source of variation is naturally occurring, and is likely by all accounts to exhibit substantial volatility in future as changing demands from a rising global middle class coincides with the impact of climate change on food supply. Our results indicate that a locally tailored policy response will be key to minimizing violence in the wake of price shocks in either direction. Incentives to work rather than to fight can prevent farmers from joining armed groups in rural areas. This could take the form of local workfare programs that shift from urban to rural regions as prices fall; or through insurance products where payouts are triggered when global prices drop to a critical level. At the same time, regionally-managed strategic buffer stocks could shelter consumers from the deleterious impacts of critically high global prices. To that end, our results could inform an early-warning prediction tool to assist in mitigating the impact of future price shocks on violence in Africa.

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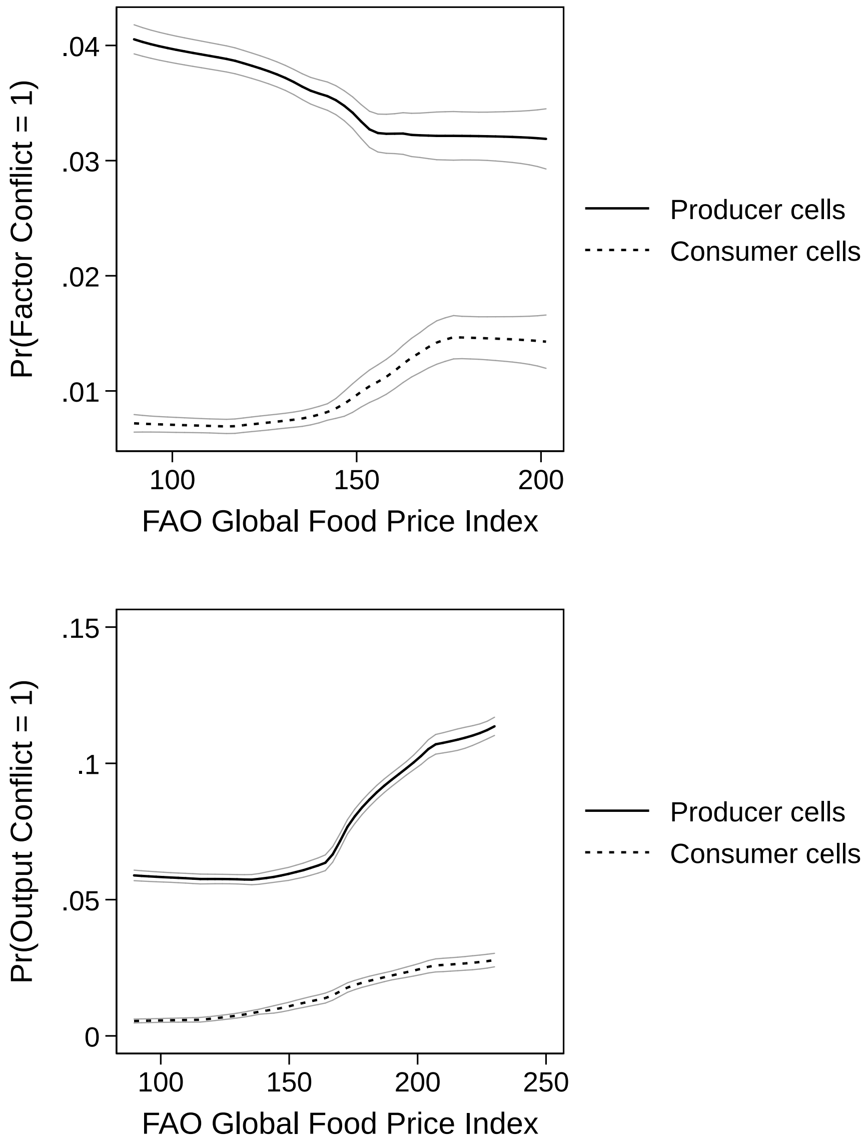
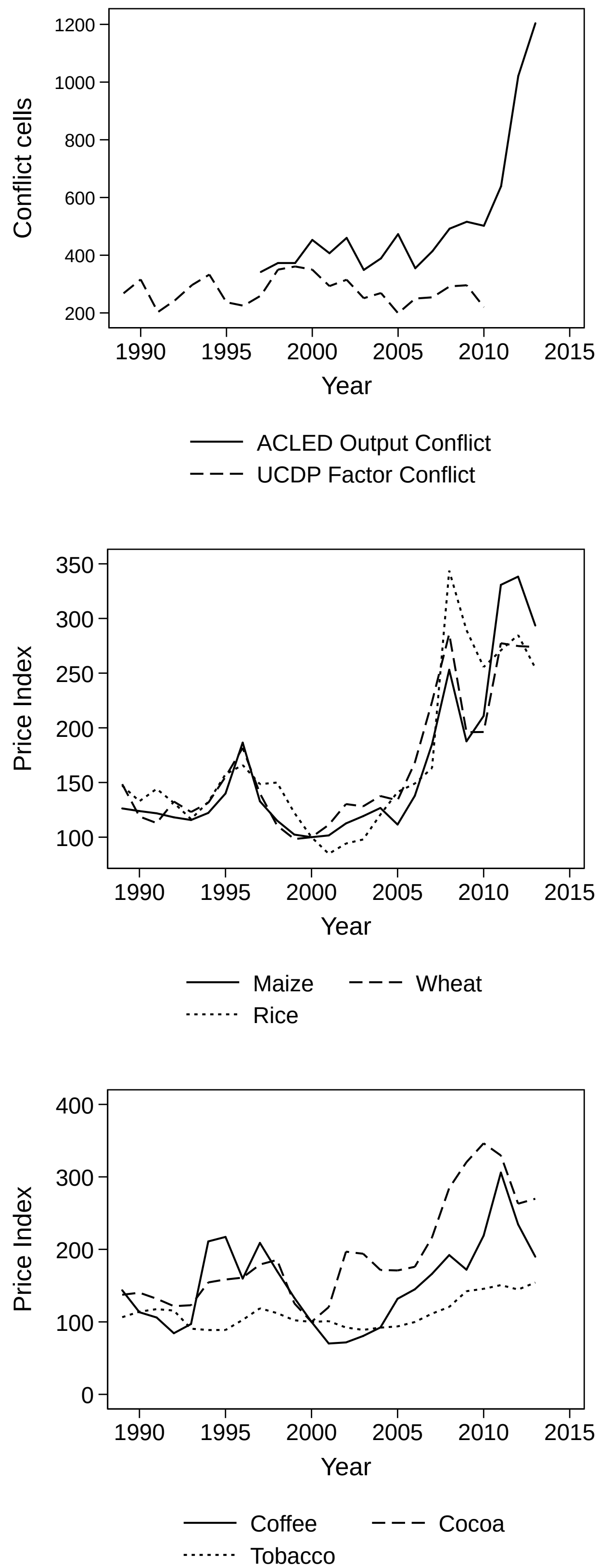
Figures

Figure 1: Factor Conflict, Output Conflict and FAO Global Food Price Index



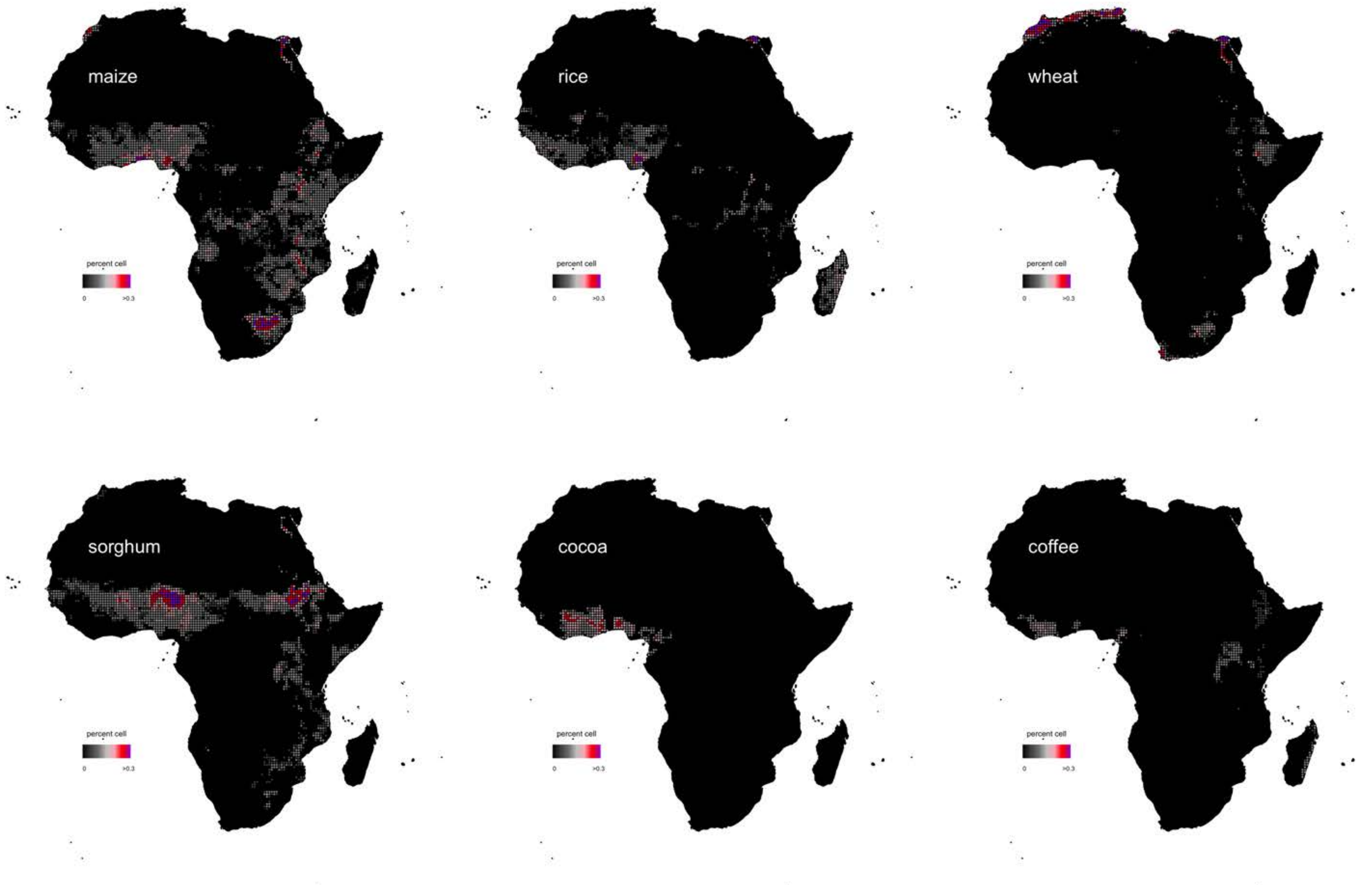
Notes: *Producer cells* are cells where cropland area > 0. *Consumer cells* are cells where cropland area $= 0$. *Factor conflict* is equal to 1 if any UCDP Factor Conflict events take place in a given cell-year, and zero otherwise. *Output conflict* is equal to 1 if any ACLED Output Conflict events take place in a given cell-year, and zero otherwise. These data are introduced formally in section 3. Epanechnikov kernel; bandwith 20.

Figure 2: Conflict and Price Variables, 1989-2013



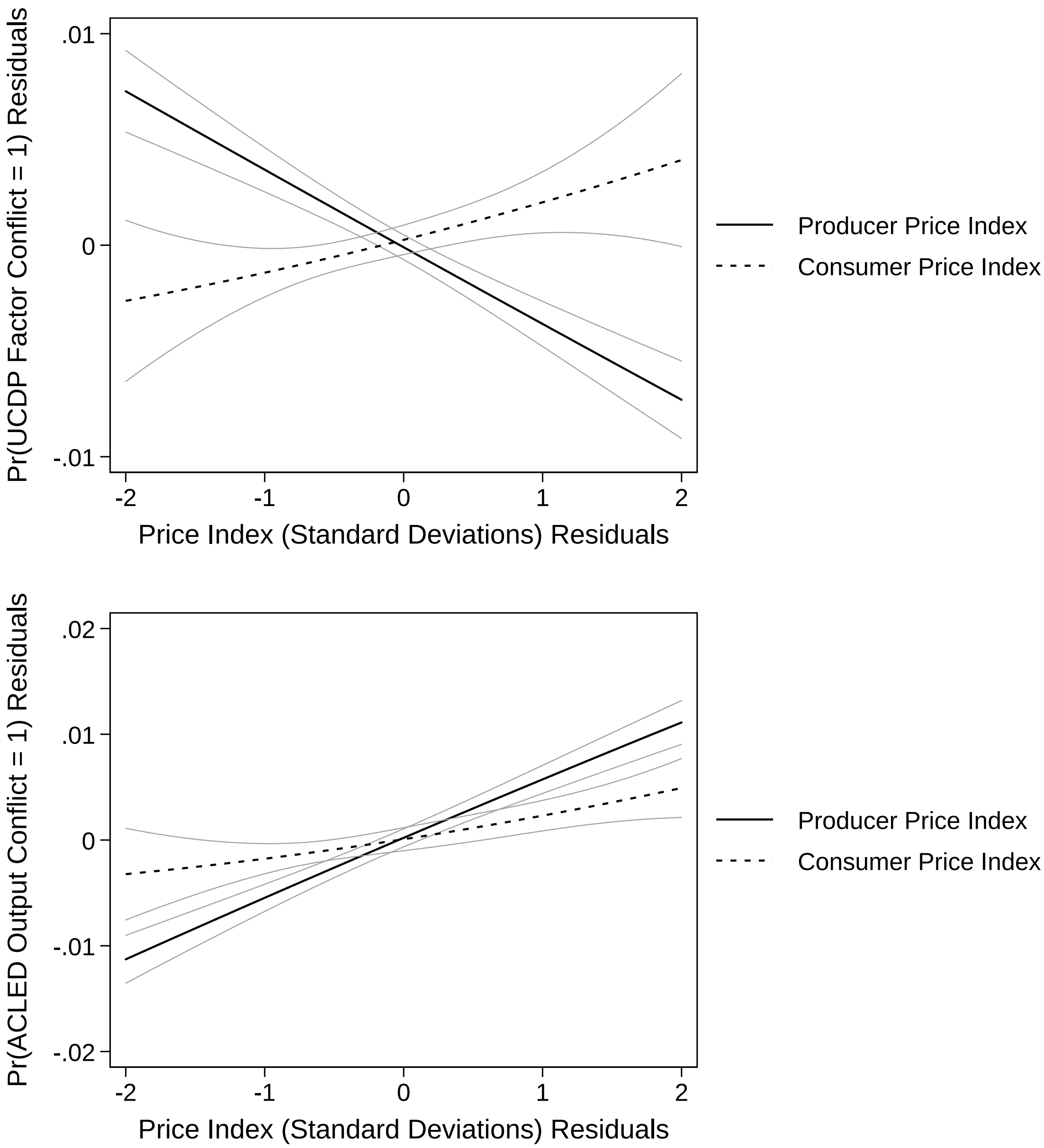
Notes: *Conflict cells* is the count of cells in which at least one conflict event took place in a given year. Price data are taken from IMF and World Bank sources (2000 = 100). See Table A1.

Figure 3: A Selection of Crop Maps



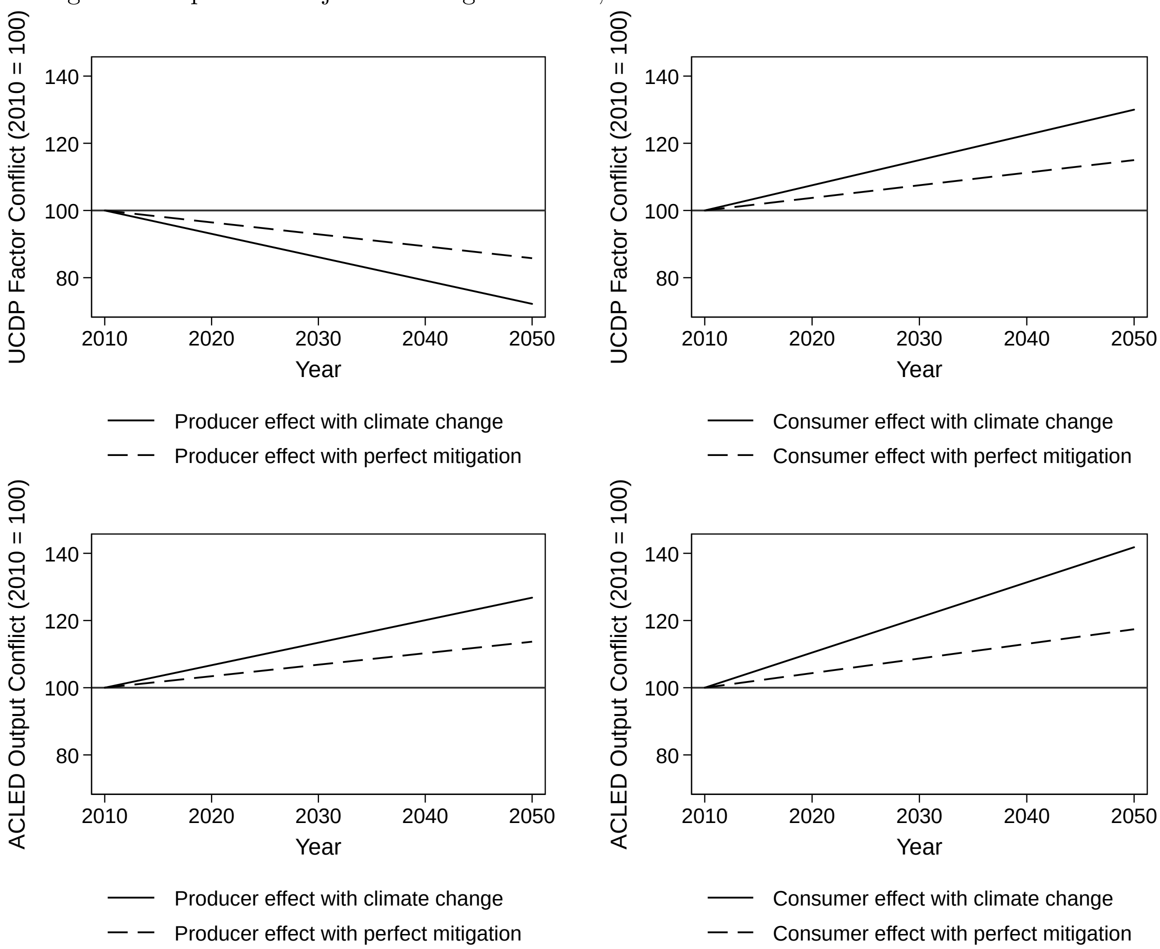
Notes: This figure shows M3 Cropland data for a selection of six crops. The *percent cell* scale indicates the share of each cell's land that is covered by a given crop

Figure 4: Impact of Prices on Factor Conflict and Output Conflict (Quadratic Fit)



Notes: In the upper panel, the outcome variable is *UCDP Factor Conflict Incidence*; in the lower panel, the outcome is *ACLED Output Conflict Incidence*. The *Price Index* variables are standardized with mean = 0 and (temporal) standard deviation = 1. The regressions also include country time trends and cell fixed effects. Quadratic fits are shown.

Figure 5: Impact of Projected Change to Maize, Rice and Wheat Prices from 2010 to 2050



Price projections are from the International Food Policy Research Institute (Nelson et al., 2010). The perfect mitigation scenario assumes all greenhouse gas emissions cease in 2000 and the climate momentum in the system is halted. Unconditional probabilities of factor conflict and output conflict in 2010 are 2.15% and 4.9% respectively. Both are normalized to 100.

Tables

Table 2: Summary statistics: 1989-2013

Variable	Mean	Std. Dev.	Min.	Max.	N
Conflict variables					
UCDP Factor Conflict					
Incidence	0.027	0.162	0	1	225038
Onset	0.014	0.119	0	1	222159
Offset	0.535	0.499	0	1	6083
ACLED Output Conflict:					
Incidence	0.05	0.219	0	1	173893
Onset	0.028	0.166	0	1	169953
Offset	0.452	0.498	0	1	8762
Output Conflict: Afrobarometer survey					
Theft in past year	0.313	0.464	0	1	67500
Violence in past year	0.131	0.337	0	1	67533
Selected cell variables					
Cropland cells	0.633	0.482	0	1	255725
Cropland area %	0.072	0.138	0	1	255725
Urban area %	0.009	0.039	0	0.87	255575
Distance to city (1000km)	0.519	0.299	0.001	1.441	255725
Luminosity	0.224	0.417	0	1	255725
Population	74415	236429	0	10740200	255725

Table 3: UCDP Factor Conflict, Producer Prices and Consumer Prices

UCDP Factor Conflict:	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Producer Price Index	-0.0042	-0.0048	-0.0024	-0.0021	0.0443	0.0314
Conley SE	0.001	0.001	0.001	0.001	0.016	0.008
p-value	0.000	0.000	0.001	0.018	0.006	0.000
Clustered SE	0.002	0.002	0.001	0.001	0.022	0.012
p-value	0.007	0.042	0.020	0.139	0.043	0.012
PPI impact (%)	-15.4	-17.7	-16.3	-14.6	8.3	5.9
Trade weight	No	Yes	No	Yes	No	Yes
Country × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.328	0.325	0.159	0.160	0.572	0.571
Observations	225038	204666	222159	202152	6083	5333
Panel B						
Producer Price Index	-0.0046	-0.0050	-0.0029	-0.0025	0.0494	0.0441
Conley SE	0.001	0.001	0.001	0.001	0.016	0.011
p-value	0.000	0.000	0.000	0.002	0.002	0.000
Clustered SE	0.001	0.002	0.001	0.001	0.023	0.017
p-value	0.001	0.010	0.006	0.045	0.029	0.009
Consumer Price Index	0.0023	0.0016	0.0015	0.0011	-0.0881	-0.0730
Conley SE	0.001	0.001	0.001	0.000	0.018	0.018
p-value	0.005	0.015	0.015	0.017	0.000	0.000
Clustered SE	0.001	0.001	0.001	0.001	0.026	0.030
p-value	0.116	0.209	0.161	0.231	0.001	0.015
PPI impact (%)	-17.2	-18.6	-20.0	-17.2	9.2	8.2
CPI impact (%)	8.6	6.0	10.2	7.8	-16.5	-13.7
Wald test: PPI = CPI						
p-value	0.000	0.000	0.002	0.001	0.001	0.007
Trade weight	No	Yes	No	Yes	No	Yes
Country × time trend	Yes	Yes	Yes	Yes	Yes	Yes
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.288	0.288	0.126	0.126	0.454	0.451
Observations	204820	204666	202298	202152	5352	5333

Note: The dependent variables are UCDP Factor Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured in terms of within-cell standard deviations. The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Conley standard errors allow for serial and spatial correlation in groups of contiguous cells. Clustered standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI (CPI) impact* indicates the effect of a one within-cell standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms.

Table 4: UCDP Factor Conflict, Prices and Luminosity

UCDP Factor Conflict:	Incidence: 1(Conflict > 0)		
	(1)	(2)	(3)
Producer Price Index	-0.0117	-0.0112	-0.0130
SE	0.006	0.007	0.008
p-value	0.054	0.094	0.102
Producer Price Index × luminosity	0.0089	0.0087	0.0073
SE	0.005	0.005	0.005
p-value	0.102	0.110	0.153
Consumer Price Index	0.0030		
SE	0.001		
p-value	0.005		
Consumer Price Index × luminosity	-0.0038	-0.0054	-0.0052
SE	0.003	0.003	0.003
p-value	0.157	0.083	0.079
PPI impact (%) at luminosity = 0	-43.5	-41.4	-48.0
PPI impact (%) at luminosity = 1	-10.6	-9.2	-20.8
CPI impact (%) at luminosity = 0	11.0		
CPI impact (%) at luminosity = 1	-3.1	-19.9	-19.2
Country × time trend	Yes	N/A	N/A
Country × year fixed effects	No	Yes	Yes
Cell FE	Yes	Yes	Yes
Extra controls	No	No	Yes
R squared	0.288	0.325	0.325
Observations	204666	204666	204666

Note: The dependent variables is UCDP Factor Conflict incidence. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured in terms of within-cell standard deviations. The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index_{t-k}. Standard errors allow for serial correlation within cells and spatial correlation within countries. *PPI (CPI) impact* indicates the effect of a one within-cell standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms. *Luminosity* = 1 if any light is visible at night from satellite images in a given cell. All specifications include controls for interaction effects between prices and population. *Extra controls* indicate controls for interactions between prices and three additional covariates: cell-level terrain, cell-level distance to the capital city, and pre-colonial political centralization, measured as the degree of jurisdictional hierarchy beyond the local level in the pre-colonial ethnic polity associated with a given cell.

Table 5: ACLED Output Conflict Incidence, Combined Producer Prices and Consumer Prices

ACLED Output Conflict:	Incidence: 1(Conflict > 0)			
	(1)	(2)	(3)	(4)
Producer Price Index	0.0076	0.0073	0.0095	0.0079
Conley SE	0.001	0.001	0.001	0.001
p-value	0.000	0.000	0.000	0.000
Clustered SE	0.003	0.003	0.003	0.002
p-value	0.007	0.008	0.000	0.001
Consumer Price Index			0.0072	0.0040
Conley SE			0.001	0.001
p-value			0.000	0.000
Clustered SE			0.002	0.001
p-value			0.000	0.001
PPI impact (%)	15.1	14.4	18.9	15.8
CPI impact (%)			14.4	8.0
Trade weight	No	Yes	No	Yes
Country × time trend	N/a	N/a	Yes	Yes
Country × year FE	Yes	Yes	No	No
Cell FE	Yes	Yes	Yes	Yes
R squared	0.399	0.397	0.373	0.371
Observations	173876	158151	158270	158151

Note: The dependent variable is a dummy for ACLED Output Conflict incidence. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured in terms of within-cell standard deviations. The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index_{t-k}. Conley standard errors allow for serial and spatial correlation in groups of contiguous cells. Clustered standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI (CPI) impact* indicates the effect of a one standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms.

Table 6: ACLED Output Conflict, Producer Prices, and Consumer Prices

ACLED Output Conflict:	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index: Food crops	0.0102	0.0084	0.0085	0.0065	0.0051	0.0083
SE	0.002	0.002	0.002	0.002	0.005	0.005
p-value	0.000	0.000	0.000	0.000	0.313	0.088
Producer Price Index: Cash crops	-0.0022	-0.0006	-0.0012	-0.0000	0.0116	0.0092
SE	0.002	0.002	0.002	0.002	0.006	0.008
p-value	0.252	0.753	0.478	0.985	0.071	0.222
Consumer Price Index	0.0074	0.0040	0.0034	0.0018	-0.1289	-0.1037
SE	0.002	0.001	0.001	0.001	0.019	0.017
p-value	0.000	0.001	0.013	0.015	0.000	0.000
PPI impact: Food crops (%)	20.3	16.6	30.1	23.0	1.1	1.8
PPI impact: Cash crops (%)	-4.4	-1.2	-4.2	-0.1	2.6	2.0
CPI impact (%)	14.7	7.9	12.0	6.4	-28.5	-23.0
Wald test: PPI Food = PPI Cash						
p-value	0.000	0.003	0.000	0.005	0.332	0.893
Trade weight	No	Yes	No	Yes	No	Yes
Country × time trend	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.373	0.371	0.167	0.166	0.445	0.437
Observations	158270	158151	154795	154677	6774	6769

Note: The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) variables are measured in terms of within-cell standard deviations. *Food crops* are crops that each represent at least 1% of caloric intake in the sample; *cash crops* are the rest (see Table A1). The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI (CPI) Impact* indicates the effect of a within-cell one standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms.

Table 7: Afrobarometer Output Conflict: Triple Difference

	Theft		Violence	
	(1)	(2)	(3)	(4)
Producer Price Index: Food crops	-0.0101	0.0284	-0.0000	0.0089
SE	0.007	0.005	0.005	0.009
p-value	0.158	0.000	0.997	0.331
Producer Price Index: Food crops × farmer	0.0082	0.0097	0.0098	0.0067
SE	0.008	0.008	0.006	0.005
p-value	0.336	0.216	0.080	0.150
Producer Price Index: Food crops × trader	0.0242	0.0258	0.0007	0.0009
SE	0.012	0.014	0.009	0.006
p-value	0.043	0.064	0.938	0.894
Producer Price Index: Cash crops	-0.0037	-0.0131	0.0044	-0.0139
SE	0.012	0.013	0.008	0.009
p-value	0.753	0.332	0.564	0.138
Producer Price Index: Cash crops × farmer	-0.0365	-0.0409	-0.0152	-0.0145
SE	0.012	0.012	0.006	0.004
p-value	0.003	0.001	0.016	0.001
Producer Price Index: Cash crops × trader	-0.0230	-0.0167	-0.0077	-0.0051
SE	0.015	0.010	0.016	0.012
p-value	0.115	0.087	0.636	0.685
Consumer Price Index	0.0401		-0.0363	
SE	0.030		0.027	
p-value	0.186		0.173	
PPI Food − PPI Cash treatment effect: farmers	0.0446	0.0506	0.0250	0.0212
SE	0.016	0.017	0.009	0.008
p-value	0.006	0.005	0.007	0.010
PPI Food − PPI Cash treatment effect: traders	0.0472	0.0425	0.0084	0.0059
SE	0.020	0.018	0.019	0.015
p-value	0.017	0.021	0.665	0.696
PPI impact: Food (%)	-3.2	9.1	-0.0	6.8
× farmer	2.6	3.1	7.5	5.1
× trader	7.7	8.2	0.5	0.7
PPI impact: Cash (%)	-1.2	-4.2	3.4	-10.6
× farmer	-11.7	-13.1	-11.6	-11.1
× trader	-7.4	-5.3	-5.9	-3.9
CPI impact (%)	12.8		-27.8	
Country × time trend	Yes	N/a	Yes	N/a
Country × period fixed effects	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Area fixed effects	Country	Cell	Country	Cell
Survey round fixed effects	Yes	Yes	Yes	Yes
R squared	0.036	0.069	0.033	0.058
Observations	39873	39036	39925	39090

Note: The dependent variables are binary responses to survey questions that ask whether individuals over the previous year (i) have been victims of theft; (ii) have been victims of physical assault. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) variables are measured in terms of within-cell standard deviations. *Food crops* are crops that each represent at least 1% of caloric intake in the sample; *cash crops* are the rest (see Table A1). The coefficients displayed include four lags, i.e., $\sum_{k=0}^{4}$ Price Index$_{t-k}$, where each t is a six-month period. *Farmer* indicates that the respondent is a commercial farmer; *trader* indicates that the respondent is a trader, hawker or vendor. Standard errors allow for serial correlation and spatial correlation within cells. *PPI (CPI) Impact (%)* indicates the effect of one within-cell standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms.

Table 8: Summary of Naive Regression Results

	UCDP Conflict	**ACLED Conflict**
Panel A: Producer Price Index		
Producer Price Index	-0.0054	0.0102
SE	(0.021)	(0.007)
p-value	0.795	0.165
impact (%)	-1.1	1.1
Panel B: Consumer Price Index		
Consumer Price Index	0.0251	0.0197
SE	(0.023)	(0.013)
p-value	0.282	0.134
impact (%)	5.1	2.2
Panel C: Both Indices		
Producer Price Index	-0.0326	-0.0048
SE	(0.023)	(0.012)
p-value	0.155	0.690
impact (%)	-6.7	-0.5
Consumer Price Index	0.0435	0.0223
SE	(0.029)	(0.019)
p-value	0.135	0.244
impact (%)	8.9	2.5

Note: This table summarizes results from six separate country-level regressions that each include controls for country fixed effects and country-specific time trends. The outcome variables respectively measure the incidence of UCDP conflict events and the combined ACLED conflict events. In *Panel A*, only the PPI is included; in *Panel B*, only the CPI is included; in *Panel C*, both the PPI and the CPI are included. The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Standard errors are clustered at the country level. *Impact (%)* indicates the effect of a within-cell one standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms.

Appendix

A Theoretical appendix

A.1 Price Stationarity

In Section 2.1, we make the assumption that $|\phi| < 1$, or that crop prices do not exhibit a unit root. This property generates the prediction that rural groups will engage in factor conflict following negative price shocks; they must believe in a positive degree of mean reversion for factor conflict to become more profitable when prices are low. A unit root would imply that price shocks are infinitely persistent, and that prices therefore follow a random walk. If this is true, then current shocks carry no information on future price changes, and the expected payoff to fighting will covary perfectly with the opportunity cost.

The augmented Dickey-Fuller test (Dickey and Fuller, 1979) allows for a unit root test that controls for serial correlation. In this context, we would fit the following model for each crop j:

$$\Delta P_{jt} = \alpha + \beta P_{jt-1} + \zeta_1 \Delta P_{jt-1} + \zeta_2 \Delta P_{jt-2} + \ldots + \zeta_k \Delta P_{jt-k} + \epsilon_t \tag{13}$$

The null hypothesis $\beta = 0$ is that crop price P_{jt} follows a unit root process. One drawback of this approach is that it is underpowered to detect stationarity, i.e., to reject the null hypothesis. Elliott et al. (1996, "ERS") develop a more efficient procedure, whereby the time series is first transformed via a generalized least squares (GLS) regression. The model in (13) is then fitted with the GLS-detrended data, providing a test with significantly greater power.

To operate this procedure, we gather price data at the monthly level from January 1980 to October 2014 in order to maximize power. We set prices in January 2000 equal to 100. The ERS procedure can test for reversion around either a stationary mean or a trend stationary mean. Figure A3 and Figure A4 present PDFs and time series plots for prices of all 11 crops in the producer index. For most crops, prices appear to exhibit mean reversion from 1980 to around 2004, during which time beliefs about price movements over the period of our analysis are likely to have been formed. Following structural breaks in 2004, some prices, e.g. maize, appear to continue reverting around a trend-stationary mean, while other processes, e.g. tobacco, appear to have a unit root. In our formal ERS test, we choose a 12 month lag structure to account for seasonality (i.e. $k = 12$) and examine whether prices exhibit a degree of stationary around a mean over the full series. We can reject a unit root for maize, rice, wheat, tea, sugar, and oil palm. Of the remaining crops, sorghum, soybean and coffee also exhibit stationarity from 1980 to 2004. Only in the cases of tobacco and cocoa do we fail to reject the null hypothesis of a unit root.[27]

The final component of this assumption is that rural groups are aware of these facts. Given that we are concerned with an environment in which farming decisions can be a matter of life and death, we assume that relatively recent price movements are retained in group memory to the extent that

[27] Choosing a lag structure determined by a Ng-Perron sequential-t method (Ng and Perron, 1995) yields the same outcome. All results are available by request.

stationarity can be detected while present.

A.2 Bargaining

Chassang and Padro i Miquel (2009) characterize the role of bargaining in a perfect information environment with offensive advantages. We begin with same set up as that described in Section 2.1, except for two differences. First, groups now begin with unequal landholdings, so that group 1 controls $\frac{N}{2} + \lambda$, and group 2 controls $\frac{N}{2} - \lambda$. Second, we make the assumption, without loss of generality, that the game has a duration of only one period.

Groups can engage in bargaining in order to avert conflict. A transfer will avert conflict if and only if neither side has an incentive to deviate following the transfer. Only then can groups credibly commit to peace (Fearon, 1995). Let T represent the transfer that group 1 can give group 2 to deter an attack. The condition for group 1 to prefer this to conflict is therefore

$$\mathbf{P} \cdot (\frac{\mathbf{N}}{2} + \lambda - \mathbf{T}) > \pi(1 - v)[\mathbf{P} \cdot \mathbf{N}].$$

The left hand side is the value of group 1's post-transfer landholding. The right hand side represents the expected payoff from launching a unilateral attack, where again π is the probability of victory for the attacker, and v is the opportunity cost of conflict.

For peace to prevail, the transfer must also generate a situation in which group 2 also prefers post-transfer peace to the expected payoff from a unilateral attack. This condition is given by

$$\mathbf{P} \cdot (\frac{\mathbf{N}}{2} - \lambda + \mathbf{T}) > \pi(1 - v)[\mathbf{P} \cdot \mathbf{N}].$$

It follows that the transfer must satisfy

$$\mathbf{P} \cdot \frac{\mathbf{N}}{2} > \pi(1 - v)[\mathbf{P} \cdot \mathbf{N}]. \tag{14}$$

The is the condition for peace in the presence of bargaining. Two observations are noteworthy. First, λ does not appear in the condition. The initial distribution of land does not determine conflict. Second, the set of parameters for which there exists a transfer T that avoids conflict is the same set of parameters for which an equal distribution of land $\frac{N}{2}$ guarantees peace. Peace is therefore only attainable if there exists no profitable unilateral deviation when both groups have equal landholdings. This holds for any initial land distribution.

The intuitive interpretation is that bargaining allows groups who are satisfied with their peaceful status quo to avoid war by transferring land to a dissatisfied group. Hence, bargaining can avoid war only in situations where one group is satisfied and the other is not. In this case of perfect information, bargaining can therefore only assuage the threat of conflict that is driven by unequal landholdings. When condition (14) does not hold, bargaining cannot affect the prospect of violence caused by the first-mover advantage.

Rearrange condition (14), conflict occurs if

$$\pi > \pi^w \equiv \frac{1}{2(1-v)}. \tag{15}$$

Peace is destabilized only if the first-mover advantage is substantial. Indeed, as noted in Chassang and Padro i Miquel (2009), there exists an offensive advantage for $\pi \in (\frac{1}{2}, \pi^s)$ in which no conflict will occur because fighting entails an opportunity cost v. The larger it is, the larger the first-mover advantage needs to be in order to generate violence.

A.3 Threshold $\tilde{\mathbf{P}}$

In this section, we characterize the threshold $\tilde{\mathbf{P}}$ below which realizations of $\mathbf{P}$ lead to conflict by applying Chassang and Padro i Miquel (2009) to our setting. Consider the continuation value of peace as the highest solution to the following equation:

$$\tilde{V}^P = F(\tilde{\mathbf{P}})\frac{1}{2}\left[\mathbb{E}(\mathbf{P}\cdot\mathbf{N} \mid \mathbf{P} < \tilde{\mathbf{P}})(1-v) + \delta V^A\right] + \Big(1 - F(\tilde{\mathbf{P}})\Big)\left[\mathbb{E}(\mathbf{P}\cdot\frac{\mathbf{N}}{2} \mid \mathbf{P} > \tilde{\mathbf{P}}) + \delta\tilde{V}^P\right].$$

With probability $F(\tilde{\mathbf{P}})$, the realization of $\mathbf{P}$ falls below $\tilde{\mathbf{P}}$, and war ensues. Solving for $\tilde{V}^P$ yields

$$\tilde{V}^P = \frac{\bar{Y}}{2(1-\delta)} - \frac{vF(\tilde{\mathbf{P}})\mathbb{E}(\mathbf{P}\cdot\frac{\mathbf{N}}{2} \mid \mathbf{P} < \tilde{\mathbf{P}})}{1-\delta\Big(1-F(\tilde{\mathbf{P}})\Big)} \tag{16}$$

The future value of playing peace in this equilibrium equals the value of playing peace forever minus the expected cost of war that will occur as soon as $\mathbf{P_t} < \tilde{\mathbf{P}}$. This is decreasing in $\tilde{\mathbf{P}}$ because the larger is the threshold $\tilde{\mathbf{P}}$, the higher the probability that conflict will occur. This increases the losses for two reasons: first, conflict occurs sooner in expectation, hence costs are less discounted; second, a higher threshold $\tilde{\mathbf{P}}$ implies that the expected value of the resources lost in the war is larger.

The optimal threshold $\tilde{\mathbf{P}}$ is the lowest value of $\mathbf{P_t}$ that satisfies (1) with equality. We substitute in (2) and (16) and rearrange to find

$$\tilde{\mathbf{P}} = \frac{\delta}{1-2\pi(1-v)}\left[(2\pi-1)\frac{\bar{\mathbf{P}}}{1-\delta} + \frac{vF(\tilde{\mathbf{P}})\mathbb{E}(\mathbf{P} \mid \mathbf{P} < \tilde{\mathbf{P}})}{1-\delta\Big(1-F(\tilde{\mathbf{P}})\Big)}\right]. \tag{17}$$

Existence of $\tilde{\mathbf{P}}$ is guaranteed because the right hand side is always strictly positive, bounded and continuous.[28] In contrast, the left hand side can take any value in $(0, +\infty)$. It follows that there are values of $\tilde{\mathbf{P}}$ that can be higher or lower than the right hand side. We can then say that, for $\pi < \pi^W$, the most efficient subgame perfect equilibrium is given by the smallest positive solution to (17). As above, for any first-mover advantage that yields $\pi > \pi^W$, there is no equilibrium that

[28] The right hand side can written as $\frac{\delta[\pi V^A - V^P]}{1-2\pi(1-v)}$, which has an upper bound $\frac{\delta\pi}{1-2\pi(1-v)}\frac{\bar{\mathbf{P}}\cdot\mathbf{N}}{1-\delta}$.

avoids war at $t = 1$, for any $\mathbf{P_1}$.

Note that the equilibrium threshold is increasing in π and δ, and decreasing in v. This implies that conflict is more likely to occur in the presence of higher offensive advantages and, interestingly, higher levels of patience. The latter can be explained by the fact that the costs of conflict are immediate, while the potential spoils are realized into the future. Finally, and intuitively, the likelihood of war is decreasing in the opportunity cost of fighting.

A.4 Deriving consumer effects of food crops, cash crops, and imported food crops

In this section, we derive how changes in the prices of food crops, cash crops, and import crops affect conflict. These results are summarized in Section 2.2 of the main text.

Food crops We begin with P_f, the price of food crops that are both produced and consumed in a given cell. Again denoting by $\mathbb{A}$ the left hand side of (5), and by $\mathbb{W}$ the right hand side, we first make the simple observation that

$$\frac{d\mathbb{A}}{dP_f} = \frac{Q(L_Q)N_f(L - L_Q)}{L_Q} > 0. \tag{18}$$

Higher food crop prices increase the payoff from appropriation.

In determining the effect of P_f on $\mathbb{W}$, we exploit a fundamental property of food: it is essential to survival, and cannot be substituted. We therefore assume without loss of generality that the price elasticity of demand is zero, and characterize the real wage rate as $\frac{w}{P_f}$. If nominal wages are rigid in the short run, we obtain:

$$\frac{d\mathbb{W}}{dP_f} = -\frac{\big[1 - Q(L_Q)\big]w}{P_f^2} < 0. \tag{19}$$

Proposition 2. *In food-producing cells, higher food prices P_f will increase the incidence of output conflict in the short run.*

The proof comes from (18) and (19). Equation (18) must be positive, as $L_Q < L$ is a necessary condition for appropriation to exist. Without it, there would be no output to appropriate. By contrast, equation (19) must be negative, yielding a clear prediction. We obtain the same qualitative outcome if nominal wages adjust fully to higher prices such that real wages are unchanged, as $\frac{d\mathbb{A}}{dP_f} - \frac{d\mathbb{W}}{dP_f} = \frac{d\mathbb{A}}{dP_f} > 0$.[29]

[29] While it is not a critical assumption, Ivanic et al. (2012) do suggest that the 2011 food price spike reduced net consumers' real wages in rural regions. However, in the longer run nominal wages will rise with higher prices by an amount determined by factor markets. Taking this into account, we can quantify the total effect of the price change on real wages as:

$$\frac{P_f(1 - Q(L_Q))\frac{dw}{dP_f} - (1 - Q(L_Q))w}{P_f^2} \tag{20}$$

where $\frac{dw}{dP_f} = \frac{1 - a_N \frac{dr}{dP_f}}{a_L}$, which is obtained from taking the total differential of equation (4). If price increases are paid

The intuition of Proposition 2 is straightforward: higher food prices increase the value of output that accrues to landowners (generating a predation effect), while simultaneously decreasing the real wage of laborers in the short run (generating an income effect). This combination of effects increases the profitability of output conflict relative to productive wage labor.[30]

Cash crops We now consider the effect of a change in P_c, the price of crops that are produced in a given cell but consumed elsewhere. The key feature of P_c is that it will not feature as a wage deflator, in contrast to the case above. It can thus be considered as a non-food crop like tobacco or cotton, or edible crops that do not contribute significantly to caloric intake, such as tea or coffee. As in the case above, higher prices will increase the value of appropriable surplus by an amount:

$$\frac{d\mathbb{A}}{dP_c} = \frac{Q(L_Q)N_c(L - L_Q)}{L_Q} > 0. \tag{21}$$

However, higher prices will also increase real wages by an amount:

$$\frac{d\mathbb{W}}{dP_c} = \big[1 - Q(L_Q)\big]\big[\frac{1 - a_N \frac{dr}{dP_c}}{a_L}\big], \tag{22}$$

which is larger than zero provided $a_N \frac{dr}{dP_c} < 1$; in other words, as long as landowners do not accrue fully the gains from higher prices.[31] We thus have a predation effect in (21) caused by the rise in value of appropriable output, but also a positive income effect in (22) caused by an increase in real wages in the productive sector. This generates an ambiguous effect overall: higher cash crop prices P_c may increase or decrease output conflict. We can say with confidence that the effect of P_c on output conflict will be lower than the effect of P_f.

Proposition 3. *The effect of cash-crop prices P_c on equilibrium output conflict is lower than the effect of food-crop prices P_f on equilibrium output conflict.*

This is because P_c and P_f both increase the value of appropriable surplus, generating a predation effect, but only P_f will reduce real wages; P_c will increase real wages provided $a_N \frac{dr}{dP_c} < 1$.

Import crops We finally consider the effect of a change in P_m, the price of imported food crops. By definition, import crop prices will only affect conflict in net consumer cells. As crop m is not produced domestically, the nominal values of both the spoils of appropriation and of the productive sector wage are unaffected by a price change. However, as both are deflated by P_m, and as $\mathbb{A} = \mathbb{W}$ in equilibrium, it follows that:

fully to land, i.e. if $a_N \frac{dr}{dP_f} = 1$, then (20) is the same as (19). As $a_N \frac{dr}{dP_f}$ falls, (20) approaches zero.

[30] If we relax the assumption of a single productive sector to include also non-agricultural productive activities, we would expect the average magnitude of the effect to be even larger. This is because, for workers in the non-farm sector, nominal wages will be slower to increase with food prices, resulting in a larger decline in real terms.

[31] Dube and Vargas (2013) find that higher coffee prices reduce conflict in Colombia for this reason. In Dal Bó and Dal Bó (2011), this is because coffee prices are relatively labor intensive.

$$\frac{d\mathbb{A}}{dP_m} = -\frac{\mathbb{A}}{dP_m^2} = \frac{d\mathbb{W}}{dP_m} = -\frac{\mathbb{W}}{dP_m^2}. \tag{23}$$

Income is spent on food, and so as prices rise, the real value of appropriation declines in concert with real wages. We therefore have no substitution effect between appropriation and wage labor: a change in P_m generates a pure income effect only.

Under what conditions will this cause consumers to engage in conflict? To answer this, we must first consider optimal responses to food price shocks. In Appendix Section A.5, we make the following points: (i) agents are unwilling to substitute food consumption intertemporally; (ii) in order to maintain food consumption in the wake of price shocks, therefore, agents must have access to savings, credit, or insurance; (iii) absent these mechanisms, agents must resort to costly coping strategies (Chetty and Looney, 2006).

We proceed in the spirit of this final point, as financial markets are relatively undeveloped in Africa. To illustrate, consider a net consumer earning a fixed nominal wage w^l from productive activities. Indirect utility $V(P_m, w^l)$ depends on the price of food items (produced elsewhere) and wage income. Consumption is determined by the budget constraint $w^l \geq P_m C$, and $C \geq \lfloor C \rfloor$; that is, consumption must be weakly greater than a target caloric intake.[32] If this restriction is violated, utility is 0.[33] We therefore assume without loss of generality that u seeks to maximize utility at time t, and we abstract from future concerns. Denote by P_m^l the price of food that prevents utility-maximizing consumers with income w^l from achieving consumption $C \geq \lfloor C \rfloor$. That is, $V(P_m^l, w^l) = 0$.

We first consider the effect of P_m on factor conflict by introducing to the environment the existence of armed group activity.[34] Armed groups offer to potential fighters a wage w^w. For (wage) fighters, expected utility is therefore given by:

$$\mathbb{E}\big[V^w(P_m, w^w, \phi_u)\big] = V(P_m, w^w) - \phi_u,$$

where $\phi_u \in (0, \phi_u^*]$ can be considered as the expected cost for consumer u of incurring physical of psychic harm in battle, and $\mathbb{E}\big[V^w(P_m, w^w, \phi_u^*)\big] = 0$ for any P_m. Importantly, ϕ_u has no direct effect on u's current budget constraint. Denote by $l_u \in \{0, 1\}$ the decision to allocate labor either to productive activities or armed fighting, where $l = 1$ implies that he chooses to work in the productive sector. The net consumer therefore faces the following problem:

$$\max_{l_u \in \{0,1\}} V_u = l_u(V(P_m, w^l)) + (1 - l_u)(V(P_m, w^w) - \phi_u). \tag{24}$$

[32]This condition may reflect the desire to avoid a poverty trap of the type discussed in Dasgupta (1997).

[33]This set up could be described with a standard Stone-Geary functional form, where $C \geq \gamma$ is the subsistence consumption requirement, and $w^l \geq p\gamma$ the budget constraint.

[34]This can be caused by a realization $\mathbf{P_{ct}} < \tilde{\mathbf{P}}$ for export cash crops such as cocoa beans, rubber, cotton or tobacco, or through another exogenous mechanism.

Rearranging the solution, he will fight if

$$V(P_m, w^w) - V(P_m, w^l) > \phi_u. \tag{25}$$

In other words, net consumers will fight if the war wage premium offsets the expected cost of fighting. This admittedly simple condition gives rise to the following observation: if $w^l \geq w^w$, then net consumers will not fight, for any P_m, ϕ_u. We obtain this result from our characterization of ϕ_u, which is strictly positive.

The more interesting case arises when $w^l < w^w$, i.e., when agents earn a wage lower than that offered by armed groups. We are specifically interested in the effect of food prices on the decision to fight in this context. It is here that our assumption of nonlinearity in consumption comes to effect. Without it, rising prices would have an ambiguous effect on u's choice: a higher P'_m would impose a proportionate drop in real wages from both war ($\frac{w^w}{P'_m}$) and productive activities ($\frac{w^l}{P'_m}$), rendering the decision unchanged (as in (23)). But if we explicitly take the target consumption constraint into account, a clearer picture emerges.

Consider a price increase to P^l_m. We can say with certainty that $P^l_m < P^w_m$, as $w^l < w^w$. This yields a "fighting condition" for net consumers as follows:

$$V(P^l_m, w^w) - V(P^l_m, w^l) > \phi_u. \tag{26}$$

The first term must be positive, as $P^l_m < P^w_m$. Wages are sufficiently high to guarantee subsistence, which yields a strictly positive utility. The second term is 0 by definition: w^l cannot return positive utility when prices reach P^l_m. The decision to fight, therefore, is determined by the condition $V(P^l_m, w^w) > \phi_u$, which is true when $\phi_u < \phi^*_u$. In other words, net consumers will fight as long as the expected value of doing so yields any utility larger than 0. Only those who expect with probability 1 to incur costs ϕ^*_u will be indifferent between fighting and not fighting.[35] Other net consumers for whom $w^l < w^w$ will join the armed group, provided they do not have access to superior outside options, including conventional consumption-smoothing instruments.

Observation 1. *In the absence of financial consumption-smoothing instruments, a realization of imported food crop price $P_{tm} \geq P^l_m$ will increase the probability that net consumers earning $w \leq w^l$ will join factor conflict groups.*

The intuition is straighforward. Higher food prices force those close to subsistence to increase their labor supply in order to maintain a target consumption level. In the absence of alternative options, this can imply incurring significant costs. It is worth reflecting on three striking empirical examples. First, de Janvry et al. (2006) find that Mexican households withdraw children from education as a response to adverse income shocks. Second, Dupas and Robinson (2012) find that transactional sex workers in Kenya engage in riskier—and more lucrative—sexual behavior following

[35] This is because $u(0) \leq E[u(0)]$: a positive probability of any utility larger than 0 dominates a guaranteed utility of 0.

an income shock caused by widespread political violence in 2007. Finally, Miguel (2005) finds that weather shocks in Tanzania lead to a large spike in "witch" killings—the murder of elderly women, typically by relatives.[36] All three of these risk-coping mechanisms share the same properties of ϕ: they are each costly, whether in terms of future income, expected health or social health, but they also each permit an expansion of the current budget constraint that allows marginal households to achieve a target consumption level. In our setting, we make the connection between these costly coping mechanisms and the decision to join armed conflict groups in battle.

The same logic can be applied to the decision to engage in output conflict. Higher food prices induce those at the margin of a target consumption level to engage in costly or risky activities in order to maintain consumption. In this case, food is not produced domestically, and consumers turn to property crime (which may also take the form of riots and looting) as a means of appropriating goods.[37] This gives an analogous prediction as follows:

Observation 2. *In the absence of financial consumption-smoothing instruments, a realization of staple food crop prices $P_{tm} \geq P^l_m$ will increase the probability that net consumers earning $w \leq w^l$ will engage in output conflict.*

A.5 Consumption and intertemporal substitution

A large literature examines the optimal response to income variation over the life cycle through the lens of consumption smoothing, or the process of saving and dissaving in order to maintain a high marginal utility of consumption.[38] However, it does not necessarily follow that perfect consumption smoothing is always optimal in context of *price* variation. If consumers expect prices to be lower in future, it may be optimal to reduce consumption in the present period. For example, consider a utility function with constant relative risk aversion:

$$U(C_{jt}) = \begin{cases} \frac{C_{jt}^{1-\sigma}}{1-\sigma} & \text{for } \sigma > 0, \sigma \neq 1 \\ \ln C_{jt} & \text{for } \sigma = 1 \end{cases}, \tag{27}$$

where C_{jt} is consumption of staple food j in time t, P_{jt} is the price of j, and σ is the risk aversion parameter. Under the assumption of perfect capital markets, intertemporal substitution can be determined by

$$\frac{C_{jt}}{C_{jt+1}} = \left(\frac{P_{jt+1}}{P_{jt}}\right)^{\frac{1}{\sigma}}.$$

Thus, consumption at t relative to future consumption is inversely related to the price at t relative to the future price. The extent to which consumers will adjust current consumption is determined

[36] Oster (2004) identifies analogous behavior in the context of temperature shocks in medieval Europe, reinforcing the case that there is little inherently "African" about costly coping strategies in the face of extreme poverty.

[37] This is akin to Gould et al. (2002), who find that lower wages for unskilled men in the US drove crime rates in the 1980s and 1990s.

[38] This follows seminal contributions on the permanent income and life cycle hypotheses by Friedman (1957) and Modigliani and Ando (1957) respectively. A recent review is provided in Jappelli and Pistaferri (2010).

by σ, the measure of risk aversion. A lower σ implies a higher substitution effect. Our assumption reflects evidence in Alem and Söderbom (2012): in the context of staple food consumption in Africa, σ is high, and consumers are less willing to substitute across periods.

This implies that consumers require liquidity to maintain a target caloric intake for a given price increase. For those with access to savings, insurance or credit, this may be achieved. For those without recourse to these instruments, relative consumption must decrease in proportion to the price change so that expenditure does not exceed nominal income earned in period t, unless other avenues are pursued.

Given that our focus is on Africa, formal financial services are not assumed to be available to a significant portion of our sample. We must then ask, how prevalent are informal smoothing instruments in developing countries? Early work by Paxson (1992) and Townsend (1994) in India, and by Udry (1994, 1995) in Nigeria, suggests a significant role for time series (savings) and cross-sectional (insurance) smoothing mechanisms, to the extent that Morduch (1995) questions the relative efficiency of publicly provided formal alternatives. However, subsequent research challenges this interpretation on two complementary counts. First, consumption appears to be strongly affected by income shocks, particularly within poor subgroups (Ravallion and Chaudhuri, 1997; Morduch, 1999; Dercon, 2004). Second, observed consumption changes may not capture the severity of household welfare costs induced by income shocks. This reflects the argument in Chetty and Looney (2006): for households that are close to subsistence (that is, a high σ case) and that do not have access to financial smoothing instruments, a target consumption level must be maintained through costly coping strategies.

B Data appendix

B.1 Price data

Table A1 presents the descriptions and sources for each raw price variable used to construct the price indices in the analysis. For each crop price, we present the exact description provided by the source. In the third column, we indicate whether the data came from the IMF *International Finance Statistics* or the World Bank *Global Economic Monitor*. In the following column we indicate whether or not the crop constituted part of the consumer index. In the final column, we indicate whether or not the crop constituted part of the producer index, and if so, whether we coded it as a food crop (which each occupy over 1% of calories consumed in a country over the series), or a cash crop (the rest). For crops with more than one potential price measure (i.e., coffee and tobacco), we compute indices using the the average value.

B.2 Alternate factor conflict measure

In robustness tests, we also operate an alternative measure of factor conflict. It consists of a subset of the Armed Conflict Location and Event Data (ACLED) project, running from 1997 to 2013 (see Raleigh et al., 2010). Like the UCDP project, ACLED records geocoded conflict events from a range of media and agency sources. Of eight conflict event categories included in the data, we include only battles in which non-state actors have won territory (category 2). This has the advantage of capturing events that are consistent our theoretical definition of factor conflict. However, with a sample mean of only 0.04%, it is a somewhat rare event in the data, reflecting the possibility that it represents a small subset of factor conflict events over the period. Broadening the measure to incorporate other battle types would run the risk of including events that fall within the scope of output conflict, as the threshold for inclusion is significantly lower than that of our preferred UCDP measure (Eck, 2012).[39]

C Additional results

C.1 Robustness of factor conflict results

Additional covariates Tables A2 to Table A4 include potentially important omitted variables. We note above that global prices are affected by weather events in producer countries. If those weather events are associated with global weather patterns, such as the El Niño Southern Oscillation (ENSO), then it could be the case that local weather events generate a correlation between global prices and the error term (Burke et al., 2015). We therefore introduce a set of weather variables. Temperature is the cell-year mean temperature in degrees celsius, based on monthly meteorological statistics from the US National Oceanic and Atmosphere Administration. Drought variables are aggregated Standardized Precipitation Index (SPI6) measures that indicate within cell-year deviations in precipitation based on monthly data. Moderate drought indicates that there were at least three consecutive months in which rainfall was more than 1 standard deviation below long term (six-month) levels; severe drought indicates that there were at least two months during which rainfall was more than 1.5 standard deviations below long term levels; and extreme drought indicates that both of these criteria were met in a cell-year. These data are provided by the Global Precipitation Climatology Centre, and converted to grid format by the PRIO-GRID project (Tollefsen et al., 2012). Table A3 presents results from specifications that include these covariates where standard errors are two-way clustered to allow for serial correlation at the cell-level and spatial correlation at the country level. Table A4 presents results with Conley standard errors that allow for serial and spatial correlation in groups of contiguous cells, which is likely to be more appropriate given the localized nature of weather patterns. We see evidence that high temperatures and severe drought do increase the probability of factor conflict incidence. Neither price index estimate is significantly affected by their inclusion.

Ross (2015) documents a large body of evidence suggesting a link between oil production and conflict. Although global oil prices are not believed to be causally related to global food prices (see Dillon and Barrett, 2015), a spurious correlation could nonetheless bias our price estimates. We therefore test three mechanisms through which oil prices can affect cell-level factor conflict in Table A4. First, higher prices in oil producing cells could increase violence by either funding

[39]This would lead to non-classical measurement error that would bias our producer price estimate toward zero.

insurgency (Collier and Hoeffler, 2004) or provoking predation (Dube and Vargas, 2013). Second, higher prices in oil producing *countries* could also strengthen a state's capacity to repel violence, generating a negative impact on conflict (Fearon and Laitin, 2003). Third, higher oil prices could increase violence through the same inflationary channel we explore in this study in the context of food. We obtain geocoded data on the location of oil fields in Africa from the PRIO Petroleum Dataset.[40] We combine this with IMF data on world oil prices to estimate a specification with three oil variables: an oil price $\times$ cell-level dummy for the presence of an oil field; an oil price $\times$ country-level dummy for oil producers; and an oil price variable that varies independently. We also add a second specification containing the cell-level interaction and country $\times$ year fixed effects. We present both models for incidence, onset and offset. We first note that the producer index estimate remains largely unaffected across specifications. The consumer price index effect is significant in the onset specification, but not in the equivalent offset model. The cell-level oil price measure has no significant effect on factor conflict; the country-level price measure has a negative effect, consistent with the state capacity interpretation of analogous results in Bazzi and Blattman (2014); and the oil price variable increases conflict incidence while controlling for production effects—a result we interpret as consistent with our consumer price effect.

Additional robustness Several alternative specifications are estimated for robustness. In Table A5, we compare models with *UCDP Factor Conflict* and *ACLED Territorial Change* as outcomes. In the first column we analyze *ACLED Territorial Change* over the maximum sample period from 1997 to 2013. Both price indices enter with the expected signs, but neither coefficient is significant at conventional levels. In columns (2) and (3) we set both side-by-side over the intersection of sample years (1997-2010). We note that PPI and CPI impacts in terms of the outcome mean are very similar: -28% and 1.1% for the ACLED measure and -25.3% and -1% for the UCDP measure. In both models PPI effects are significant; the p-values for the CPI effects are similar; and difference between the PPI and CPI effects are also significant. This exercise indicates that the main results of this study are likely not driven by fixed features of the two data-collection organizations.

In Table A6, we aggregate our spatial unit of analysis from 0.5 degree $\times$ 0.5 degree cells to 1 degree $\times$ 1 degree cells. The outcome variable now indicates that a conflict event took part in a given cell of roughly 110km $\times$ 110km, and the producer price index is averaged over four of the baseline cells. This loss of information can be expected to push the estimates toward zero. However, this exercise can also address concerns that the high degree of spatial resolution is artificially increasing the magnitude of the producer price coefficients. In addition to this adjustment, we explicitly model spatial dependence in the producer price index. This is achieved by first generating a symmetric weighting matrix W, which ascribes a value of 1 to all eight contiguous cells, and a value of 0 otherwise. A spatial lag of producer prices is then created by multiplying this matrix by the vector of observations.[41] This is a spatial Durbin model (Anselin, 2013), and is applied in a similar

[40]The dataset contains information on all known on-shore oil and gas deposits throughout the world. It can be accessed at https://www.prio.org/Data/Geographical-and-Resource-Datasets/Petroleum-Dataset

[41]We also include the sum of temporal lags in the spatial lag variable.

set-up by Harari and La Ferrara (2014) in their disaggregated analysis of weather and conflict in Africa. We also include Conley standard errors (in groups of contiguous cells) as well as two-way clustered errors (at the level of the cell and the country-year). A unit increase in the spatial lag variable reflects a unit increase in any of the eight contiguous cells. The results indicate the following: although standard errors are larger, the PPI still increases factor conflict incidence and duration in our preferred country × year models; producer prices in neighboring 1 degree cells do not significantly influence conflict in a given cell; and the CPI effects are largely unaffected given that they vary at the country-year level.

In Table A7, we present results from a fixed effects conditional logit estimation. The main results are qualitatively similar, although now higher producer prices significantly reduce the *duration* of factor conflict only, and the opposite is true for consumer prices, as in the main specification. These specifications include a common trend and no country × year fixed effects in order for the models to converge. The sample size is also significantly smaller, as the CL estimator discards cells that exhibit no change in the outcome variable over the series.

C.2 Robustness of output conflict results

Table A8 presents results from the baseline output conflict regression that includes country × year fixed effects and therefore excludes the CPI variable. These results reinforce the main findings, and are discussed in Section 5 of the main text.

In Table A9 and Table A10, we reintroduce the weather and oil price variables that are described above. Firstly, we note that the main results are mostly unchanged. Higher food crop prices lead to large and significant increases in output conflict in food-producing areas. Higher cash crop prices lead to negligible changes in output conflict in cash crop producing areas. The coefficients for the consumer price index are large and significant in the weather regressions, but are smaller and not significant when all three oil price variables are included. Interestingly, however, higher oil prices for consumers—i.e., controlling for production at both the cell and country level—significantly increase output conflict incidence and duration, a result we interpret as consistent with our model. We also find that higher oil prices have an additional effect on output conflict in oil-producing cells.

In Table A11 we repeat the spatial Durbin model aggregated to 1 degree cells and including both Conley and two-way clustered standard errors. Models with and without CYFEs are presented for each one of the the incidence, onset and offset outcomes. Again, $\beta^{pc} < \beta^{pf}$ in all incidence and onset regressions, while the coefficients are not significantly different in the offset regressions. In most cases, a higher PPI for food crops increases output conflict and higher PPI for cash crops reduces output conflict. The CPI has a large effect on incidence, onset and duration. Focusing on the CYFE regressions in columns (2), (4) and (6), we see some evidence that a rising PPI for food crops in neighboring cells *reduces* conflict duration, perhaps reflecting the possibility that output conflict shifts to neighboring cells when crop prices are higher there.

In Table A12 we present results from a FE conditional logit estimator with and without trade weights for each of the three outcomes. On this occasion we lose around three quarters of our observations, as cells that do not exhibit changes in the dependent variable over the series do not contribute to the log-likelihood. P-values are slightly above the 10% threshold on the PPI food crop coefficient when trade weights are not included, while estimates are extremely noisy when weights are used. The cash crop producer price index is never associated with more violence. The coefficients on the the two PPI measures are significantly different (in the expected direction) in the incidence and onset regressions when trade weights are not used. The consumer price index estimate is also consistent with the LPM results.

Is output conflict just "food riots"? Our theory above predicts that the effect of higher consumer prices on output conflict is positive because agents will engage in such conflict as a means of maintaining a target consumption level. However, work by Bellemare (2015) and others show that higher food prices can cause "food riots" that may be driven as much by a desire to provoke government policy changes than by a desire to directly appropriate property from others, an interpretation supported by Hendrix and Haggard (2015) and Bates and Carter (2012), who find that governments frequently alter policies in favor of consumers in the wake of price shocks. Food riots in the context above will occur in urban centers where government authorities can be expected plausibly to respond. Output conflict, according to our theory, can happen anywhere there are poor consumers and where there is appropriable property. We therefore interact our consumer price index with two measures of urbanization in order to detect these differences. The first measures the share of each cell area that is classified as urban by the SEDAC project at Columbia University introduced above; the second captures the population share that is classified as urban. Evidence of a significant interaction term is consistent with this protest riot explanation (although it does not rule out the possibility that output conflict is more pervasive in cities). However, a significant coefficient on the CPI term strongly suggests that the overall effect is not explained fully by protest riots.

Results are given in Table A13. In column (1), both the interaction term *CPI* × *urban area and* the *CPI* term are significantly different from zero (the respective p-values are 0.00 and 0.03). In the 90th percentile of urbanization, a standard deviation rise in the CPI in increases output conflict by 12%; when urban area is equal to zero, the same change still increases output conflict by 4.6%. In column (2), we add CYFEs and remove the CPI term. We see that, while the interaction term is still significant, it is also smaller. In columns (3) and (4) the interaction term *CPI* × *urban population* is used as a substitute, and we find that its effect is statistically indistinguishable from zero irrespective of whether CYFEs are included. Taken together, these results suggest that the main output conflict results are not driven by urban food riots or protests designed to create unrest and agitate for policy reforms. Output conflict occurs in non-urban as well as urban areas, consistent with our main theoretical prediction. The additional effect in urban areas is consistent not only with the idea that consumers demonstrate to provoke policy changes, but also with the idea that output conflict is higher in cities due to a wider prevalence of appropriable property.

C.3 Comparisons between output and factor conflict

In Table A14 we compare our results on output conflict and on factor conflict over the same period in order to investigate whether the contrasting impact of producer food crop prices on both outcomes can be fully explained by the different sample periods or data collection projects. We compare the effects of all three price variables—PPI for food crops, PPI for cash crops and the CPI—on all three outcome variables: *ACLED Output Conflict*, *ACLED Territorial Change* and *UCDP Factor Conflict*. For each outcome we run two specifications: one using the full available sample (1997-2013 for ACLED variables and 1989-2010 for UCDP variables), and one using only the intersection of years (1997-2010). In all cases we limit our attention to conflict incidence.

Consistent with the model's predictions, we note that (i) only in the *ACLED Territorial Change* and *UCDP Factor Conflict* regressions is there a significant difference between the (total) PPI effect and the CPI effect; (ii) only in the output conflict regression is there a significantly positive effect of the food crop PPI on conflict. We see clear differences in the effects of the PPI variables between columns (1) and (3) (both ACLED outcomes over the same period) and between (2) and (6) (*ACLED Output Conflict* and *UCDP Factor Conflict*) over the same period.

C.4 Afrobarometer results

To merge the Afrobarometer data with our main dataset, we make two important adjustments. First, we replace years with half-year periods as our unit of temporal analysis. Our indices are thus constructed with average world prices over six months (January to June and July to December).[42] This expands the number of temporal data points from 9 to 13. Second, we aggregate our spatial unit of analysis from 0.5 degree cells to 1 degree cells. This ensures that regressions with cell fixed effects will have more statistical power. Without aggregation, we would have to discard information on 9,855 observations from cells that feature in only one round. Moreover, 15,424 observations would be from cells that only feature in two periods. By aggregating, we discard only 3,929 single-cell observations, while only 8,100 observations are in cells that feature twice.

Food prices and self-reported poverty In Table A15, we examine the effect of the producer and consumer price indices on three different self-reported poverty measures. In columns (1)-(4), the outcome variable is a poverty index that combines answers to survey questions on how often the respondent has gone without access to food, water, health, electricity and income. We split the 25-point index so that zero indicates below or at the median score, and a value of 1 indicates above the median. In columns (5)-(8) the outcome variable indicates that the household has frequently gone without income over the preceding year, and in columns (9)-(12) the outcome variable indicates that the household has frequently gone without food over the preceding year. We estimate linear probability models for all specifications.

In column (1), we control for survey round fixed effects, country fixed effects, a country-specific time trend, the age of the respondent, age squared, education level, gender, urban or rural primary

[42]We adjust our lags accordingly in regressions

sampling unit, and a vector of 0.5 degree cell-level crop-specific land area shares to ensure that the producer price index is not picking up time-invariant features of agricultural production. We cluster standard errors at the cell level. A one standard deviation increase in the CPI raises the probability that a respondent is above the median poverty index value by 12.2%, or from 45% to 50.5% at the mean. The equivalent results for income poverty and food poverty in columns (4) and (7) confirm that households do not adjust exclusively to higher food prices via a substitution effect.

In column (1) we also see that an equivalent change in the PPI has a negligible effect on the overall poverty index, a result at odds with our prediction. One possible explanation for this finding is that higher producer prices alleviate poverty only for those in the agricultural sector. Our micro-level data permits a direct test of this hypothesis, as respondents are asked to list their occupation in the first three rounds of the survey. Of the 59,871 respondents, 17,999 (30%) are farmers of any type. This allows us to include an interaction between the PPI and an indicator that the respondent is a farmer. We add country $\times$ period fixed effects and present alternative specifications with country fixed effects (2) and cell fixed effects (3). The results in either case are more clear: higher producer prices significantly lower the probability that farmers report above-median poverty index scores relative to non-farmers, although the magnitude ($\sim 1\%$) is not large. Overall, these results broadly consistent with the assumptions of our theory: higher food prices represent negative income shocks for consumers, and positive shocks for producers.

Validation tests In Table A16, we test for consistency between our cell-level and individual-level measures of output conflict. Our individual measures are binary responses to survey questions that ask whether individuals over the previous year (i) have been victims of theft; (ii) have been victims of physical assault; (iii) have partaken in "protest marches", which may take the form of demonstrations or of mass output conflict in the form of riots or looting. We regress each indictor on our cell-level *ACLED Output Conflict Variable* in three specifications: one bivariate, one with survey round fixed effects and country fixed effects, and one that adds the *UCDP Factor Conflict* measure in order to determine if the survey measures are also (or instead) capturing factor conflict. In eight of the nine specifications, the survey measures correlate significantly with *ACLED Output Conflict Variable*. The exception is the bivariate protest variable regression. The *UCDP Factor Conflict* variable does not enter significantly in any specification.

Appendix Figures

Figure A1: Cell Resolution

Note: each point is the centroid of a 0.5 × 0.5 degree cell.

Figure A2: FAO Global Food Price Index Series from 1999-2013

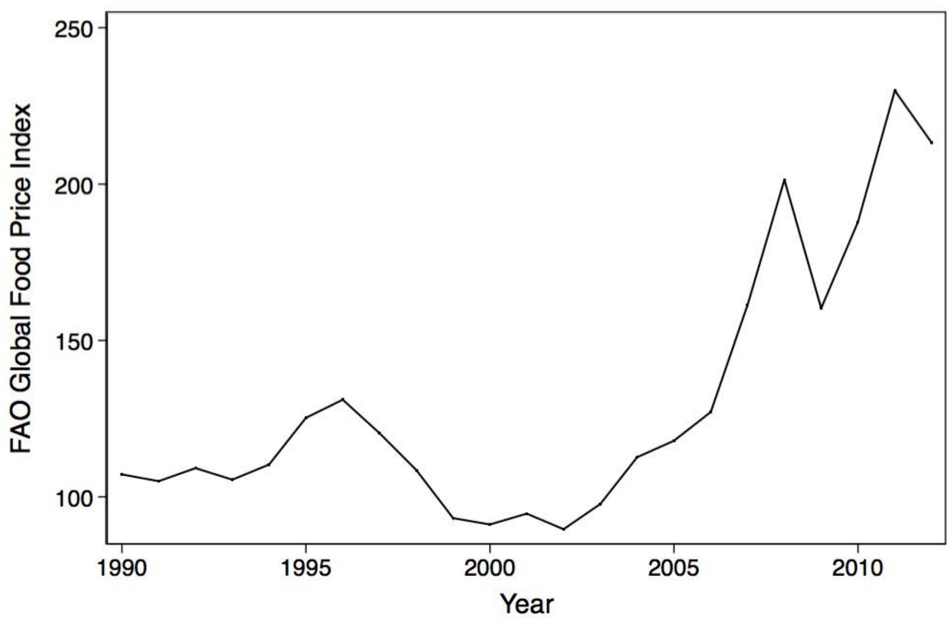


Figure A3: Crop Price Probability Density Functions (Kernel Estimation)

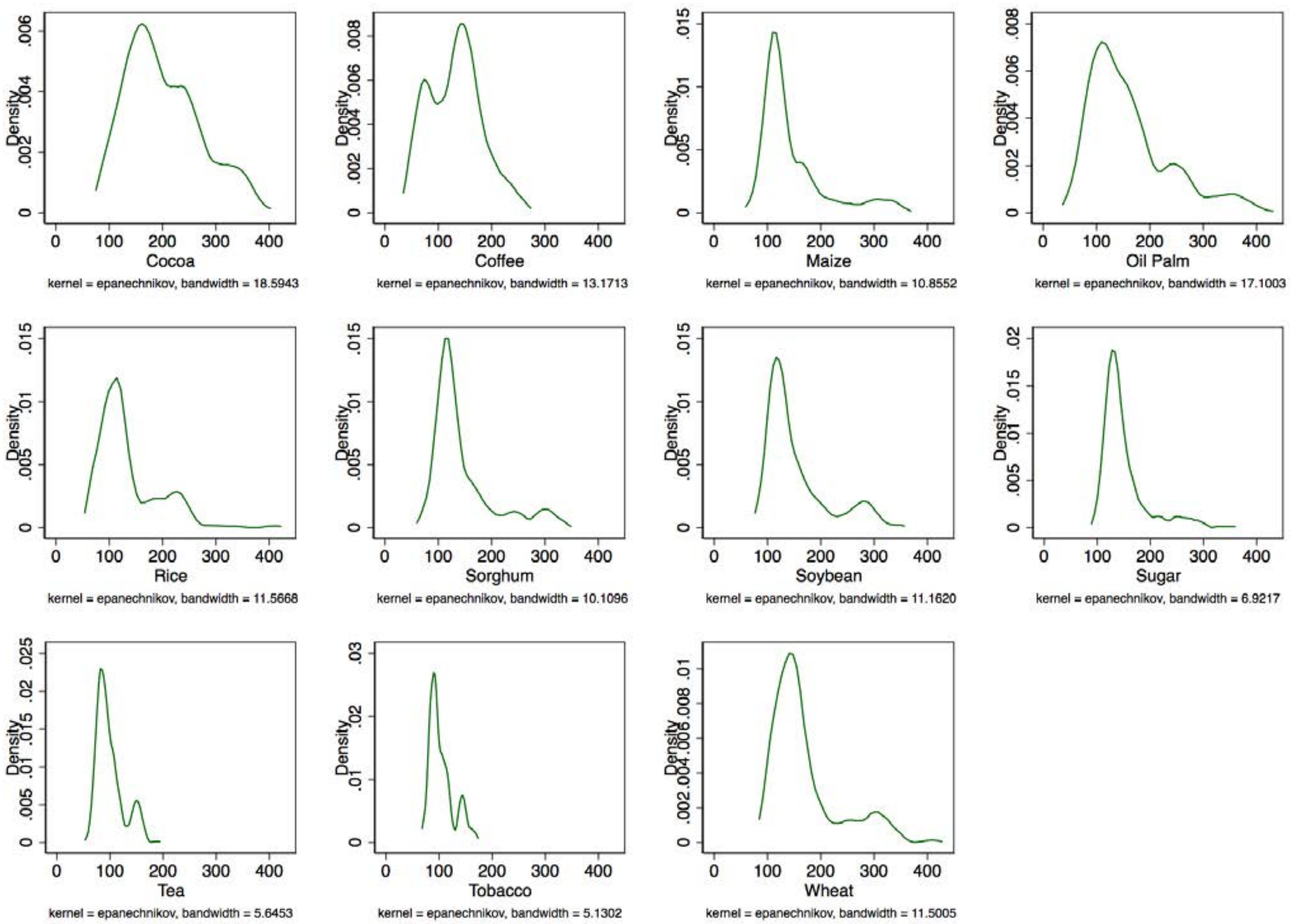
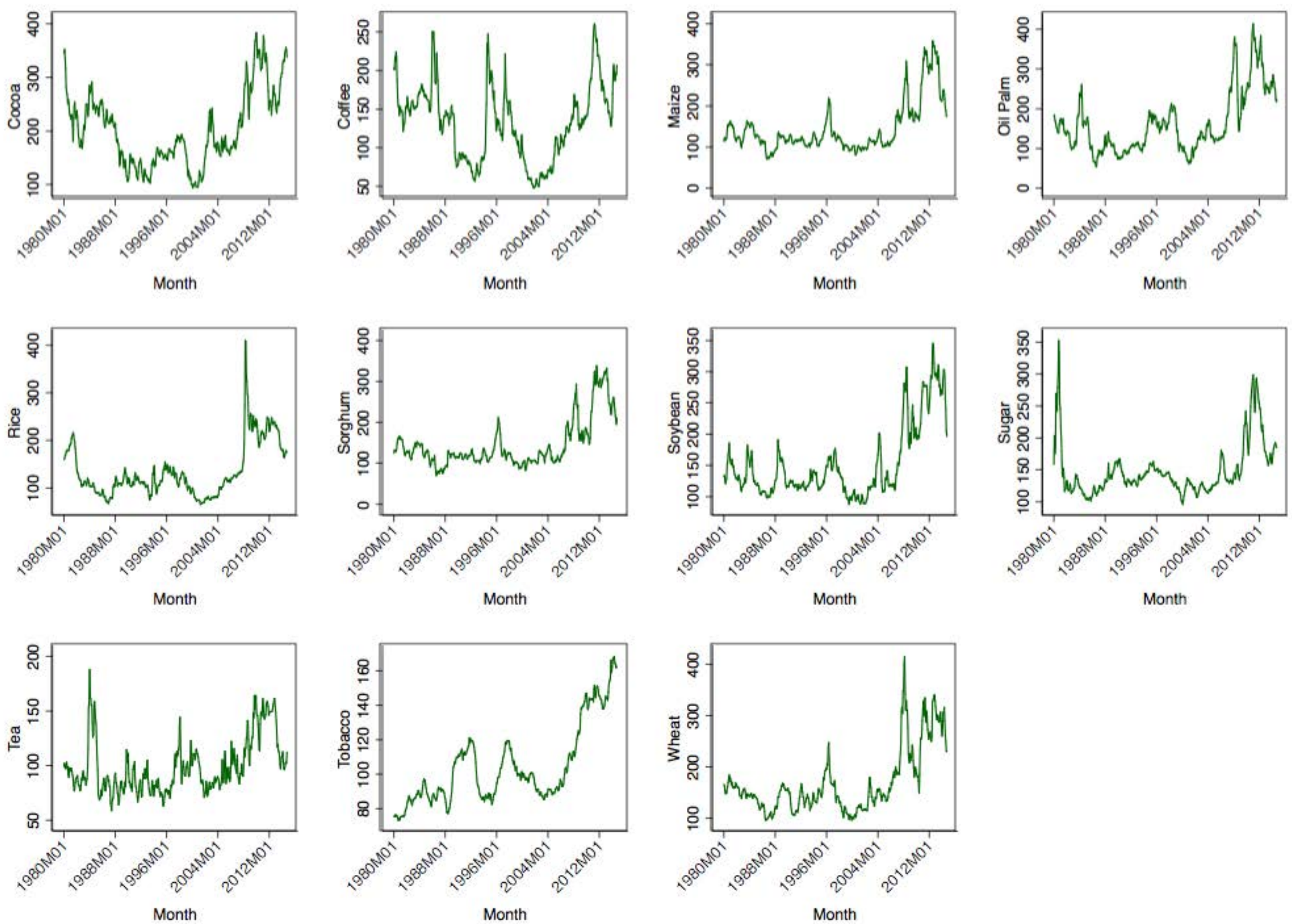


Figure A4: Crop Price Monthly Series (2000M01 = 100)



Appendix Tables

Table A1: Price Variables

Crop	Description (from source)	Source	Consumer crop	Producer crop
Bananas	Central American and Ecuador, FOB U.S. Ports, US$ per metric ton	IMF	Yes	
Barley	Canadian No.1 Western Barley, spot price, US$ per metric ton	IMF	Yes	
Cocoa	International Cocoa Organization cash price, CIF US and European ports, US$ per metric ton	IMF	Yes	Yes (cash)
Coconut oil	Philippines/Indonesia, bulk, c.i.f. Rotterdam, US$ per metric ton	WB	Yes	
Coffee 1	Robusta, International Coffee Organization New York cash price, ex-dock New York, US cents per pound	IMF	Yes	Yes (cash)
Coffee 2	Other Mild Arabicas, International Coffee Organization New York cash price, ex-dock New York, US cents per pound	IMF	Yes	Yes (cash)
Maize	U.S. No.2 Yellow, FOB Gulf of Mexico, U.S. price, US$ per metric ton	IMF	Yes	Yes (food)
Nuts	Groundnuts (peanuts), 40/50 (40 to 50 count per ounce), cif Argentina, US$ per metric ton	IMF	Yes	
Oil palm	Malaysia Palm Oil Futures (first contract forward) 4-5 percent FFA, US$ per metric ton	IMF	Yes	Yes (food)
Olive	Olive Oil, extra virgin less than 1% free fatty acid, ex-tanker price U.K., US$ per metric ton	IMF	Yes	
Orange	Miscellaneous oranges CIF French import price, US$ per metric ton	IMF	Yes	
Rice	5 percent broken milled white rice, Thailand nominal price quote, US$ per metric ton	IMF	Yes	Yes (food)
Sorghum	Sorghum (US), no. 2 milo yellow, f.o.b. Gulf ports, US$ per metric ton	WB	Yes	Yes (food)
Soybean	Chicago Soybean futures contract (first contract forward) No. 2 yellow and par, US$ per metric ton	IMF	Yes	Yes (food)
Sugar 1	Free Market, Coffee Sugar and Cocoa Exchange (CSCE) contract no.11 nearest future position, US cents per pound	IMF	Yes	Yes (food)
Sugar 2	U.S. import price, contract no.14 nearest futures position, US cents per pound (Footnote: No. 14 revised to No. 16)	IMF	Yes	Yes (food)
Sunflower	Sunflower Oil, US export price from Gulf of Mexico, US$ per metric ton	IMF	Yes	
Tea	Mombasa, Kenya, Auction Price, From July 1998, Kenya auctions, Best Pekoe Fannings. Prior, London auctions, c.i.f. U.K. warehouses, US cents per kilogram	IMF	Yes	Yes (cash)
Tobacco	Any origin, unmanufactured, general import , cif, US$ per metric ton	WB	No	Yes (cash)
Wheat	No.1 Hard Red Winter, ordinary protein, FOB Gulf of Mexico, US$ per metric ton	IMF	Yes	Yes (food)

Table A2: UCDP Factor Conflict Results with Weather Covariates

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	-0.0050	-0.0048	-0.0024	-0.0021	0.0431	0.0302
SE	0.002	0.002	0.001	0.001	0.017	0.012
p-value	0.010	0.041	0.049	0.142	0.011	0.016
Consumer Price Index	0.0017		0.0011		-0.0690	
SE	0.001		0.001		0.030	
p-value	0.190		0.229		0.023	
Temperature	0.0063	0.0093	0.0014	0.0051	-0.0222	0.0003
SE	0.003	0.004	0.002	0.002	0.041	0.052
p-value	0.060	0.038	0.509	0.036	0.590	0.995
Moderate drought	-0.0036	-0.0027	-0.0014	-0.0023	0.0197	0.0169
SE	0.005	0.005	0.003	0.003	0.064	0.061
p-value	0.486	0.571	0.675	0.462	0.757	0.782
Severe drought	0.0058	0.0076	0.0022	0.0026	-0.1607	-0.1937
SE	0.005	0.005	0.003	0.003	0.099	0.108
p-value	0.217	0.096	0.438	0.353	0.107	0.075
Extreme drought	-0.0028	0.0039	0.0003	0.0019	0.0600	-0.0283
SE	0.004	0.004	0.003	0.002	0.056	0.052
p-value	0.526	0.305	0.907	0.414	0.285	0.587
PPI impact (%)	-18.4	-17.6	-16.9	-14.4	8.1	5.7
CPI impact (%)	6.1		7.6		-12.9	
Wald test: PPI = CPI						
p-value	0.000		0.002		0.010	
Country × time trend	Yes	N/A	Yes	N/A	Yes	N/A
Country × year fixed effects	No	Yes	No	Yes	No	Yes
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.288	0.325	0.126	0.160	0.371	0.492
Observations	204336	204336	201821	201821	4612	4479

Note: The dependent variables are UCDP Factor Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured in terms of within-cell standard deviations. The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI (CPI) impact* indicates the effect of a one standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms. *Temperature* is the cell-year mean temperature in degrees celsius; *moderate drought* indicates that there were at least three consecutive months in which rainfall was more than 1 standard deviation below long term (six-month) levels; *severe drought* indicates that there were at least two months during which rainfall was more than 1.5 standard deviations below long term levels; and *extreme drought* indicates that both of these criteria were met in a cell-year.

Table A3: UCDP Factor Conflict Results with Weather Covariates, Conley SEs

UCDP Factor Conflict:	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	-0.0050	-0.0048	-0.0024	-0.0021	0.0431	0.0302
Conley SE	0.001	0.001	0.001	0.001	0.011	0.008
p-value	0.000	0.000	0.002	0.020	0.000	0.000
Consumer Price Index	0.0017		0.0011		-0.0690	
Conley SE	0.001		0.000		0.018	
p-value	0.014		0.021		0.000	
Temperature	0.0063	0.0093	0.0014	0.0051	-0.0222	0.0003
Conley SE	0.002	0.002	0.001	0.002	0.028	0.042
p-value	0.000	0.000	0.242	0.001	0.420	0.994
Moderate drought	-0.0036	-0.0027	-0.0014	-0.0023	0.0197	0.0169
Conley SE	0.004	0.003	0.003	0.003	0.062	0.056
p-value	0.337	0.436	0.604	0.374	0.752	0.762
Severe drought	0.0058	0.0076	0.0022	0.0026	-0.1607	-0.1937
Conley SE	0.003	0.003	0.002	0.002	0.096	0.095
p-value	0.081	0.018	0.344	0.261	0.093	0.041
Extreme drought	-0.0028	0.0039	0.0003	0.0019	0.0600	-0.0283
Conley SE	0.003	0.003	0.002	0.002	0.047	0.045
p-value	0.365	0.170	0.871	0.333	0.199	0.531
PPI impact (%)	-18.4	-17.6	-16.9	-14.4	8.1	5.7
CPI impact (%)	6.1		7.6		-12.9	
Wald test: PPI = CPI						
p-value	0.002		0.001		0.005	
Country × time trend	Yes	N/A	Yes	N/A	Yes	N/A
Country × year fixed effects	No	Yes	No	Yes	No	Yes
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.288	0.325	0.126	0.160	0.453	0.572
Observations	204336	204336	201822	201822	5329	5329

Note: The dependent variables are UCDP Factor Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured in terms of within-cell standard deviations. The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Standard errors allow for serial and spatial correlation in groups of contiguous cells. *PPI (CPI) impact* indicates the effect of a one standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms. *Temperature* is the cell-year mean temperature in degrees celsius; *moderate drought* indicates that there were at least three consecutive months in which rainfall was more than 1 standard deviation below long term (six-month) levels; *severe drought* indicates that there were at least two months during which rainfall was more than 1.5 standard deviations below long term levels; and *extreme drought* indicates that both of these criteria were met in a cell-year.

Table A4: UCDP Factor Conflict Results with Oil Covariates

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	-0.0052	-0.0048	-0.0024	-0.0021	0.0348	0.0301
SE	0.002	0.002	0.001	0.001	0.015	0.012
p-value	0.011	0.046	0.058	0.152	0.018	0.013
Consumer Price Index	0.0017		0.0033		-0.0238	
SE	0.002		0.002		0.040	
p-value	0.473		0.059		0.551	
Oil price × oil cell	0.0000	0.0000	0.0000	-0.0000	-0.0007	-0.0006
SE	0.000	0.000	0.000	0.000	0.000	0.001
p-value	0.635	0.666	0.972	0.892	0.106	0.263
Oil price × oil country	-0.0001		-0.0001		0.0004	
SE	0.000		0.000		0.001	
p-value	0.034		0.048		0.537	
Oil price	0.0075		0.0022		-0.0600	
SE	0.004		0.003		0.046	
p-value	0.050		0.423		0.190	
PPI impact (%)	-19.3	-17.9	-16.9	-14.3	6.5	5.6
CPI impact (%)	6.3		22.6		-4.5	
Wald test: PPI = CPI						
p-value	0.007		0.000		0.235	
Country × time trend	Yes	N/A	Yes	N/A	Yes	N/A
Country × year fixed effects	No	Yes	No	Yes	No	Yes
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.288	0.325	0.126	0.160	0.380	0.493
Observations	204666	204666	202151	202151	4614	4479

Note: The dependent variables are UCDP Factor Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured in terms of within-cell standard deviations. The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI (CPI) impact* indicates the effect of a one standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms. *Oil cell* is a dummy indicating the presence of an oil field in a given cell, and *oil country* is a dummy indicating that there is an oil field in the given country.

Table A5: Alternative Factor Conflict Comparisons

	Incidence 1(Conflict > 0)		
	(1)	(2)	(3)
Producer Price Index	-0.0003	-0.0012	-0.0068
SE	0.000	0.001	0.002
p-value	0.540	0.098	0.003
Consumer Price Index	0.0004	0.0000	-0.0003
SE	0.000	0.000	0.001
p-value	0.169	0.874	0.835
PPI impact (%)	-6.5	-28.0	-25.3
CPI impact (%)	8.8	1.1	-1.0
Wald test: PPI = CPI			
p-value	0.154	0.083	0.002
Country × time trend	Yes	Yes	Yes
Cell fixed effects	Yes	Yes	Yes
Sample	1997-2013	1997-2010	1997-2010
Dep. Var.	Territory	Territory	Factor
Source	ACLED	ACLED	UCDP
R squared	0.115	0.139	0.359
Observations	158151	130242	130242

Note: The dependent variable *Territory* is taken from the ACLED project, and is equal to 1 if a battle takes place in which territorial control is transferred. The dependent variable *Factor* is UCDP Factor Conflict. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured in terms of within-cell standard deviations. The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI (CPI) impact* indicates the effect of a within-cell one standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms.

Table A6: UCDP Factor Conflict: 1 Degree Aggregation with Spatially Lagged PPI

UCDP Factor Conflict:	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	-0.0039	-0.0054	-0.0007	-0.0016	0.0205	0.0250
Conley SE	0.002	0.002	0.002	0.002	0.014	0.012
p-value	0.069	0.010	0.718	0.388	0.146	0.042
Clustered SE	0.003	0.003	0.002	0.002	0.016	0.013
p-value	0.194	0.072	0.717	0.397	0.212	0.057
Producer Price Index $\times$ W	-0.0001	-0.0021	-0.0021	-0.0024	0.0090	0.0030
Conley SE	0.003	0.003	0.002	0.003	0.015	0.016
p-value	0.979	0.958	0.409	0.354	0.557	0.849
Clustered SE	0.004	0.005	0.003	0.004	0.018	0.017
p-value	0.984	0.974	0.486	0.503	0.621	0.859
Consumer Price Index	-0.0019		0.0005		-0.0810	
Conley SE	0.001		0.001		0.020	
p-value	0.138		0.625		0.000	
Clustered SE	0.002		0.002		0.027	
p-value	0.449		0.785		0.003	
PPI impact (%)	-5.4	-7.6	-1.5	-3.6	3.2	3.9
PPI $\times W$ impact (%)	-0.1	0.2	-4.6	-5.4	1.4	0.5
CPI impact (%)	-2.6		1.1		-12.7	
Wald test: PPI = CPI						
p-value	0.639		0.642		0.004	
Country $\times$ time trend	Yes	N/A	Yes	N/A	Yes	N/A
Country $\times$ year fixed effects	No	Yes	No	Yes	No	Yes
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.325	0.411	0.170	0.249	0.280	0.431
Observations	54010	53968	53887	53843	3571	3417

Note: The dependent variables are UCDP Factor Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured in terms of within-cell standard deviations. The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Conley standard errors allow for serial and spatial correlation in groups of contiguous cells. Clustered standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI (CPI) impact* indicates the effect of a one standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms. W is a spatial weighting matrix; the spatial lag $PPI \times W$ measures the PPI in all eight neighboring cells.

Table A7: UCDP Factor Conflict: Conditional Fixed Effects Logit

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	-0.0871	-0.0842	-0.0823	-0.0751	0.3461	0.3385
SE	0.089	0.060	0.055	0.048	0.117	0.085
p-value	0.328	0.159	0.136	0.115	0.003	0.000
Consumer Price Index	-0.0132	-0.0345	-0.0102	-0.0356	-0.7986	-0.7811
SE	0.120	0.138	0.116	0.129	0.143	0.216
p-value	0.913	0.802	0.930	0.783	0.000	0.000
Wald test: PPI = CPI						
p-value	0.671	0.791	0.629	0.811	0.000	0.000
Trade weight	No	Yes	No	Yes	No	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R squared	0.002	0.003	0.003	0.004	0.033	0.030
Observations	37268	37136	32532	32408	3907	3890

Note: All regressions estimated with conditional fixed effect logit estimator. The dependent variables are UCDP Factor Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured in terms of within-cell standard deviations. The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Standard errors allow for serial and spatial correlation at the country level.

Table A8: ACLED Output Conflict and Disaggregated Producer Prices

ACLED Output Conflict:	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index: Food crops	0.0083	0.0077	0.0072	0.0062	0.0076	0.0092
Conley SE	0.001	0.001	0.001	0.001	0.002	0.002
p-value	0.000	0.000	0.000	0.000	0.001	0.000
Clustered SE	0.003	0.002	0.002	0.002	0.004	0.004
p-value	0.001	0.002	0.000	0.001	0.061	0.026
Producer Price Index: Cash crops	-0.0026	-0.0019	-0.0014	-0.0008	0.0118	0.0160
Conley SE	0.001	0.001	0.001	0.001	0.004	0.004
p-value	0.023	0.123	0.223	0.491	0.001	0.000
Clustered SE	0.002	0.002	0.002	0.002	0.007	0.008
p-value	0.225	0.404	0.461	0.676	0.082	0.043
PPI Impact: Food crops	16.6	15.3	25.5	21.9	1.7	2.0
PPI Impact: Cash crops	-5.2	-3.7	-5.0	-2.9	2.6	3.5
Wald test: PPI Food = PPI Cash						
p-value	0.000	0.002	0.000	0.004	0.522	0.370
Trade weight	No	Yes	No	Yes	No	Yes
Country × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.399	0.397	0.195	0.196	0.545	0.550
Observations	173876	158151	169933	154677	7410	6625

Note: The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) variables are measured in terms of within-cell standard deviations. *Food crops* are crops that each represent at least 1% of caloric intake in the sample; *cash crops* are the rest (see Table A1). The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Conley standard errors allow for serial and spatial correlation in groups of contiguous cells. Clustered standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI Impact* indicates the effect of a within-cell one standard deviation rise in producer prices on the outcome variable in percentage terms.

Table A9: ACLED Output Conflict, Producer Prices and Consumer Prices: with Weather Covariates

ACLED Output Conflict:	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index: Food crops	0.0084	0.0077	0.0065	0.0062	0.0079	0.0090
SE	0.002	0.002	0.002	0.002	0.005	0.004
p-value	0.000	0.002	0.000	0.001	0.110	0.028
Producer Price Index: Cash crops	-0.0008	-0.0018	-0.0001	-0.0008	0.0099	0.0165
SE	0.002	0.002	0.002	0.002	0.008	0.008
p-value	0.695	0.426	0.937	0.695	0.190	0.037
Consumer Price Index	0.0038		0.0018		-0.0960	
SE	0.001		0.001		0.018	
p-value	0.001		0.016		0.000	
Temperature	-0.0143	0.0063	-0.0070	0.0050	0.1436	0.0600
SE	0.005	0.005	0.003	0.003	0.036	0.045
p-value	0.002	0.181	0.046	0.150	0.000	0.185
Moderate drought	0.0218	0.0152	0.0140	0.0080	-0.0932	-0.0487
SE	0.007	0.007	0.005	0.005	0.065	0.067
p-value	0.001	0.020	0.007	0.100	0.149	0.470
Severe drought	0.0008	-0.0051	0.0018	-0.0031	-0.0345	0.1210
SE	0.005	0.005	0.004	0.004	0.092	0.103
p-value	0.872	0.310	0.654	0.417	0.707	0.242
Extreme drought	0.0099	0.0024	0.0118	0.0049	-0.0351	-0.0246
SE	0.007	0.006	0.005	0.005	0.065	0.069
p-value	0.155	0.696	0.028	0.303	0.589	0.722
PPI impact: Food crops (%)	16.6	15.3	22.8	21.9	1.7	2.0
PPI impact: Cash crops (%)	-1.6	-3.5	-0.5	-2.8	2.2	3.6
CPI impact (%)	7.6		6.5		-21.3	
Wald test: PPI Food = PPI Cash						
p-value	0.003	0.002	0.005	0.004	0.763	0.325
Country × time trend	Yes	N/a	Yes	N/a	Yes	N/a
Country × year fixed effects	No	Yes	No	Yes	No	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.372	0.397	0.167	0.197	0.442	0.551
Observations	157896	157896	154424	154424	6760	6618

Note: The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) variables are measured in terms of within-cell standard deviations. *Food crops* are crops that each represent at least 1% of caloric intake in the sample; *cash crops* are the rest (see Table A1). The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI (CPI) Impact* indicates the effect of a one standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms. *Temperature* is the cell-year mean temperature in degrees celsius; *moderate drought* indicates that there were at least three consecutive months in which rainfall was more than 1 standard deviation below long term (six-month) levels; *severe drought* indicates that there were at least two months during which rainfall was more than 1.5 standard deviations below long term levels; and *extreme drought* indicates that both of these criteria were met in a cell-year.

Table A10: ACLED Output Conflict, Producer Prices and Consumer Prices: with Oil Covariates

ACLED Output Conflict:	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index: Food crops	0.0077	0.0070	0.0061	0.0058	0.0065	0.0073
SE	0.002	0.002	0.002	0.002	0.004	0.004
p-value	0.001	0.003	0.001	0.002	0.131	0.074
Producer Price Index: Cash crops	-0.0009	-0.0019	-0.0002	-0.0008	0.0084	0.0168
SE	0.002	0.002	0.002	0.002	0.007	0.008
p-value	0.649	0.396	0.915	0.671	0.235	0.040
Consumer Price Index	0.0006		0.0008		-0.0414	
SE	0.003		0.002		0.029	
p-value	0.861		0.726		0.149	
Oil price × oil cell	0.0002	0.0002	0.0001	0.0001	0.0003	0.0004
SE	0.000	0.000	0.000	0.000	0.000	0.000
p-value	0.000	0.000	0.000	0.000	0.169	0.126
Oil price × oil country	-0.0001		-0.0001		-0.0004	
SE	0.000		0.000		0.001	
p-value	0.136		0.212		0.485	
Oil price	0.0191		0.0097		-0.1117	
SE	0.009		0.007		0.053	
p-value	0.025		0.146		0.034	
PPI impact: Food crops (%)	15.2	13.8	21.6	20.4	1.4	1.6
PPI impact: Cash crops (%)	-1.8	-3.7	-0.7	-3.0	1.9	3.7
CPI impact (%)	1.2		3.0		-9.2	
Wald test: PPI Food = PPI Cash						
p-value	0.004	0.004	0.007	0.006	0.783	0.242
Country × time trend	Yes	N/a	Yes	N/a	Yes	N/a
Country × year fixed effects	No	Yes	No	Yes	No	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.372	0.397	0.166	0.196	0.442	0.550
Observations	158151	158151	154677	154677	6769	6625

Note: The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) variables are measured in terms of within-cell standard deviations. *Food crops* are crops that each represent at least 1% of caloric intake in the sample; *cash crops* are the rest (see Table A1). The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI (CPI) Impact* indicates the effect of a one standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms. *Oil cell* is a dummy indicating the presence of an oil field in a given cell, and *oil country* is a dummy indicating that there is an oil field in the given country.

Table A11: ACLED Output Conflict: 1 Degree Aggregation with Spatially Lagged PPI

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index: Food crops	0.0060	0.0066	0.0107	0.0113	0.0035	-0.0024
Conley SE	0.004	0.003	0.004	0.003	0.005	0.004
p-value	0.093	0.013	0.003	0.000	0.493	0.539
Clustered SE	0.004	0.004	0.003	0.003	0.006	0.006
p-value	0.174	0.119	0.001	0.000	0.533	0.683
Producer Price Index: Cash crops	-0.0106	-0.0127	-0.0090	-0.0109	0.0183	0.0152
Conley SE	0.005	0.004	0.004	0.004	0.007	0.008
p-value	0.019	0.001	0.034	0.007	0.009	0.059
Clustered SE	0.004	0.004	0.004	0.005	0.008	0.009
p-value	0.011	0.004	0.042	0.017	0.029	0.105
Producer Price Index: Food crops $\times W$	0.0090	0.0007	0.0058	-0.0002	0.0193	0.0273
Conley SE	0.004	0.003	0.004	0.003	0.009	0.006
p-value	0.022	0.804	0.135	0.943	0.031	0.000
Clustered SE	0.005	0.005	0.005	0.005	0.014	0.011
p-value	0.078	0.885	0.254	0.961	0.156	0.011
Producer Price Index: Cash crops $\times W$	0.0159	0.0010	0.0158	0.0031	-0.0211	-0.0129
Conley SE	0.005	0.005	0.005	0.005	0.008	0.012
p-value	0.001	0.845	0.001	0.554	0.009	0.282
Clustered SE	0.005	0.008	0.006	0.007	0.013	0.015
p-value	0.002	0.901	0.005	0.647	0.105	0.389
Consumer Price Index	0.0255		0.0162		-0.1769	
Conley SE	0.002		0.001		0.012	
p-value	0.000		0.000		0.000	
Clustered SE	0.004		0.003		0.021	
p-value	0.000		0.000		0.000	
PPI impact: Food crops (%)	4.3	4.8	12.0	12.6	0.6	-0.4
PPI impact: Cash crops (%)	-7.7	-9.2	-10.1	-12.2	3.3	2.8
PPI $\times$ W impact: Food crops (%)	6.5	0.5	6.5	-0.3	3.5	5.0
PPI $\times$ W impact: Cash crops (%)	11.6	0.7	17.7	3.5	-3.8	-2.4
CPI impact (%)	18.5		18.1		-32.3	
Wald test: PPI Food = PPI Cash						
p-value	0.008	0.003	0.001	0.000	0.157	0.136
Country $\times$ time trend	Yes	N/a	Yes	N/a	Yes	N/a
Country $\times$ year fixed effects	No	Yes	No	Yes	No	Yes
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.417	0.488	0.207	0.284	0.313	0.495
Observations	41735	41701	41644	41608	5407	5240

Note: The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) variables are measured in terms of within-cell standard deviations. *Food crops* are crops that each represent at least 1% of caloric intake in the sample; *cash crops* are the rest (see Table A1). The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI (CPI) Impact* indicates the effect of a one standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms. W is a spatial weighting matrix; the spatial lag $PPI \times W$ measures the PPI in all eight neighboring cells.

Table A12: ACLED Output Conflict: Conditional Fixed Effects Logit

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index: Food crops	0.0292	-0.0085	0.0304	0.0068	-0.0000	0.0486
SE	0.020	0.045	0.019	0.039	0.016	0.036
p-value	0.139	0.849	0.107	0.860	0.998	0.179
Producer Price Index: Cash crops	-0.0221	-0.0084	-0.0161	-0.0098	0.0492	0.0274
SE	0.021	0.026	0.019	0.022	0.020	0.034
p-value	0.301	0.749	0.394	0.655	0.013	0.420
Consumer Price Index	0.3646	0.2601	0.1572	0.0906	-0.6686	-0.5787
SE	0.150	0.161	0.106	0.119	0.170	0.208
p-value	0.015	0.105	0.138	0.447	0.000	0.005
Wald test: PPI = CPI						
p-value	0.073	0.999	0.114	0.764	0.035	0.714
Trade weight	No	Yes	No	Yes	No	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R squared	0.063	0.055	0.058	0.055	0.148	0.133
Observations	42092	42058	37870	37837	5462	5457

Note: All regressions estimated with conditional fixed effect logit estimator. The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) variables are measured in terms of within-cell standard deviations. The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Standard errors allow for serial and spatial correlation at the country level.

Table A13: ACLED Output Conflict, Producer Prices and Consumer Prices: Urban Riots

ACLED Output Conflict:	Incidence: 1(Conflict > 0)			
	(1)	(2)	(3)	(4)
Producer Price Index: Food crops	0.0036	0.0029	0.0078	0.0071
SE	0.002	0.002	0.002	0.003
p-value	0.088	0.175	0.002	0.005
Producer Price Index: Cash crops	-0.0003	-0.0015	-0.0006	-0.0018
SE	0.002	0.002	0.002	0.002
p-value	0.898	0.497	0.761	0.407
Consumer Price Index	0.0023		0.0039	
SE	0.001		0.001	
p-value	0.032		0.001	
Consumer Price Index × urban area	0.2071	0.2038		
SE	0.049	0.048		
p-value	0.000	0.000		
Consumer Price Index × urban population			0.0000	0.0000
SE			0.000	0.000
p-value			0.384	0.378
CPI impact (%) at urban area = 0	4.6			
CPI impact (%) at urban area 90th pctile	12.0	7.3		
CPI impact (%) at urban pop = 0			7.8	
CPI impact (%) at urban pop 90th pctile			8.2	0.4
Country × time trend	Yes	N/a	Yes	N/a
Country × year fixed effects	No	Yes	No	Yes
Cell FE	Yes	Yes	Yes	Yes
R squared	0.373	0.399	0.371	0.397
Observations	158049	158049	158151	158151

Note: The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) variables are measured in terms of within-cell standard deviations. *Food crops* are crops that each represent at least 1% of caloric intake in the sample; *cash crops* are the rest (see Table A1). The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI (CPI) Impact* indicates the effect of one within-cell standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms. *Urban area* is the percentage of a given cell area classified as urban; *urban population* is the percentage of a given cell's population classified as living in urban areas.

Table A14: Comparison of Effects on Output Conflict and Factor Conflict Incidence

	ACLED Output Conflict		ACLED Territorial Change		UCDP Factor Conflict	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index: Food crops	0.0084	0.0017	0.0002	-0.0001	-0.0042	-0.0058
SE	0.002	0.003	0.000	0.000	0.002	0.002
p-value	0.000	0.519	0.256	0.242	0.041	0.017
Producer Price Index: Cash crops	-0.0006	0.0013	-0.0008	-0.0030	-0.0025	-0.0040
SE	0.002	0.003	0.001	0.002	0.002	0.002
p-value	0.753	0.653	0.312	0.055	0.110	0.049
Consumer Price Index	0.0040	-0.0001	0.0003	0.0000	0.0016	-0.0003
SE	0.001	0.001	0.000	0.000	0.001	0.001
p-value	0.001	0.921	0.226	0.986	0.206	0.826
PPI Impact: Food crops	16.6	3.4	4.9	-2.9	-15.6	-21.3
PPI Impact: Cash crops	-1.2	2.6	-19.6	-71.7	-9.4	-14.6
CPI impact (%)	7.9	-0.2	7.9	0.1	5.9	-1.0
Wald test: PPI (total) = CPI						
p-value	0.260	0.437	0.218	0.037	0.000	0.000
Wald test: PPI Food = PPI Cash						
p-value	0.003	0.925	0.229	0.067	0.547	0.599
Sample	1997-2013	1997-2010	1997-2013	1997-2010	1989-2010	1997-2010
Country × time trend	Yes	Yes	Yes	Yes	Yes	Yes
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.371	0.395	0.115	0.140	0.288	0.359
Observations	158151	130242	158151	130242	204666	130242

Note: All three dependent variables measure conflict incidence: 1(Conflict > 0). The dependent variable *Territorial Change* is taken from the ACLED project, and is equal to 1 if a battle takes place in which territorial control is transferred. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) variables are measured in terms of within-cell standard deviations. *Food crops* are crops that each represent at least 1% of caloric intake in the sample; *cash crops* are the rest (see Table A1). The coefficients displayed include two lags, i.e., $\sum_{k=0}^{2}$ Price Index$_{t-k}$. Standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI (CPI) Impact* indicates the effect of one within-cell standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms.

Table A15: Afrobarometer: Prices and Poverty

	Poverty: index			Poverty: income			Poverty: food		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Producer Price Index	-0.0004	0.0011	0.0094	-0.0022	-0.0021	0.0036	-0.0049	-0.0015	0.0059
SE	0.002	0.004	0.007	0.002	0.002	0.005	0.002	0.003	0.006
p-value	0.878	0.766	0.191	0.197	0.382	0.471	0.020	0.619	0.284
Producer Price Index × farmer		-0.0046	-0.0048		-0.0007	-0.0013		-0.0029	-0.0040
SE		0.002	0.002		0.002	0.001		0.002	0.002
p-value		0.023	0.010		0.648	0.375		0.160	0.054
Consumer Price Index	0.0552			0.0531			0.0599		
SE	0.033			0.021			0.027		
p-value	0.091			0.014			0.029		
PPI impact (%)	-0.1	0.2	2.1	-0.4	-0.3	0.6	-1.4	-0.4	1.7
PPI impact × farmer (%)		-1.0	-1.1		-0.1	-0.2		-0.8	-1.1
CPI impact (%)	12.2			8.6			17.4		
Country × time trend	Yes	N/a	N/a	Yes	N/a	N/a	Yes	N/a	N/a
Country × period fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area FE	Country	Country	Cell	Country	Country	Cell	Country	Country	Cell
Survey round fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.130	0.156	0.202	0.145	0.148	0.180	0.107	0.119	0.160
Observations	66946	41133	41121	66543	40860	40848	66836	41059	41047

Note: The dependent variables as follows: *Poverty: index* indicates that a household has an above-median score on a 25-point poverty index that measures access to food, water, health, electricity and income; *Poverty: income* indicates that a household has frequently gone without income over the preceding year; *Poverty: food* indicates that a household has frequently gone without food over the preceding year. Columns (1), (4) and (6) have larger sample sizes as data on occupation is not available in all rounds. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) variables are measured in terms of within-cell standard deviations. *Food crops* are crops that each represent at least 1% of caloric intake in the sample; *cash crops* are the rest (see Table A1). The coefficients displayed include four lags, i.e., $\sum_{k=0}^{4}$ Price Index$_{t-k}$, where each t is a six-month period. Standard errors allow for serial and spatial correlation within cells. *PPI (CPI) Impact* indicates the effect of one within-cell standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms.

Table A16: Afrobarometer: Output Conflict Validation Tests

	Theft			Violence			Protest		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ACLED Output Conflict	0.0758	0.0447	0.0428	0.0594	0.0251	0.0223	0.0106	0.0166	0.0167
SE	0.012	0.011	0.012	0.010	0.007	0.007	0.009	0.007	0.007
p-value	0.000	0.000	0.000	0.000	0.000	0.001	0.252	0.013	0.014
UCDP Factor Conflict			0.0104			0.0165			-0.0027
SE			0.022			0.021			0.016
p-value			0.641			0.437			0.867
ACLED Output Conflict (%)	24.2	14.3	13.7	45.4	19.2	17.1	7.8	12.2	12.2
UCDP Factor Conflict (%)			3.3			12.6			-2.0
Country fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Survey round fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
R squared	0.006	0.021	0.022	0.006	0.023	0.024	0.000	0.021	0.021
Observations	67500	67500	67500	67533	67533	67533	67028	67028	67028

Note: The dependent variables are binary responses to survey questions that ask whether individuals over the previous year (i) have been victims of theft; (ii) have been victims of physical assault; (iii) have partaken in "protest marches". The coefficients displayed include lags that cover the previous year, i.e., $\sum_{k=0}^{2} \text{Conflict}_{t-k}$, where each t is a six-month period. Standard errors allow for serial and spatial correlation within cells.