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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. 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 insurgents, yielding an unclear relationship. 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 standard deviation rise in producer prices lowers the probability of conflict by around 15% 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. We posit that higher food 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 as well as food-consuming 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. In the first, we find that a one standard deviation increase in world food prices raises output conflict in food-producing cells by 17%. By contrast, for an equivalent change in the relevant world prices, no such 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* (Hirshleifer, 1991), 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,

[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.

and have no effect on the onset of new conflicts.

Recent advances in data quality have permitted a shift in focus away from the country-level toward studies that exploit variation at the subnational level. Focusing on Africa, articles by Berman and Couttenier (2015) and Fjelde (2015) suggest that declining export revenues from crop agriculture increase the incidence of conflict battles, while Harari and La Ferrara (2014) show that droughts in agricultural areas during critical growing periods have a similar effect. All three studies are consistent with the opportunity cost and state capacity mechanisms. By contrast, Berman et al. (2017) show that higher mineral prices increase conflict in areas containing mines—a result that aligns with the predation effect and a related *feasibility* mechanism, whereby armed groups who capture valuable mineral deposits are consequently equipped to launch attacks elsewhere. Analyzing violence in 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. Their results are consistent with Dal Bó and Dal Bó (2011), who propose that positive price shocks to capital-intensive sectors will increase conflict through the predation channel, whereas shocks to labor-intensive sectors will reduce conflict through the opportunity cost channel.

Our analysis complements this literature by reconciling existing ambiguity and by establishing novel relationships. First, focusing on our factor conflict results, we identify a negative impact of real income on conflict battles using plausibly exogenous variation in a manner that is not easily explained by alternative accounts. This is because any confounding variable would have to affect conflict through the same opposing channels across food-producing and food-consuming cells. This feature is related to Dube and Vargas (2013), who uncover opposing effects of shocks to different sectors in order to distinguish between two sets of mechanisms. In our case, the strategy allows us to cleanly isolate the opportunity cost channel from the observationally similar state capacity channel by identifying opposing effects within a state from the same price shock in a given period, thus overcoming a longstanding problem in the literature. Moreover, we do so by combining high resolution data covering the entire continent of Africa over the 25 years from 1989 to 2013.

In addition to allowing for the identification of causal mechanisms, our simultaneous estimation of consumer and producer price effects also calls for a revision of the established link between crop prices and conflict more generally. Dube and Vargas (2013), Berman and Couttenier (2015), Fjelde (2015), and, at the country-level, Bazzi and Blattman (2014) and Brückner and Ciccone (2010), all find that rising crop prices lead to fewer conflict events. We show, however, that it is essential to also consider the real income effects of consumer crop prices before drawing general conclusions. For example, we estimate that the overall impact of the food price spike from 2004-2008 on the average cell-level probability of conflict battles in Africa was actually positive, comprising of a -13% producer effect and a $+19\%$ consumer effect. We also show that it is not possible to detect these opposing effects with precision when we aggregate our data to the country level.

Third, we depart from the existing subnational literature by distinguishing theoretically and empirically between two different types of violence: factor conflict and output conflict. We posit that the same producer price shock will affect these conflict types in opposing directions. An alternative testable implication—say, for example, that the same shock affects both types in the same direction—would be susceptible to the charge that both conflict measures in fact approximate the same underlying process, and that the fundamental distinction is not empirically relevant. In providing a clear falsification test, we introduce to the literature the idea that certain shocks can affect different types of conflict in opposing ways, and that failing to account for this may produce misleading results.[3] Moreover, our findings that food prices increase output conflict differentially in food-producing areas adds a new dimension to our understanding of the predation motive, which is generally associated with the control of rents from oil and mineral deposits.

Fourth, we provide a micro-level validation of the main output conflict results using household survey data on interpersonal crime and physical assault. To the best of our knowledge, this is the first case of micro-level conflict data being used to verify results derived from geocoded conflict event data. We view this as reassuring, given the insights that have been generated with the geocoded event data in the existing literature.

Finally, our results align with recent patterns of conflict that are at odds with existing studies in the literature, including, for example, the "Arab Spring" unrest in North Africa and the Middle East during the 2011-12 food price spike. In Section 2, we illustrate our model with a discussion of two civil wars that occurred in Côte d'Ivoire since the turn of the century—one, largely rural, that followed historically low crop prices; and another, more urban, that followed historically high crop prices. We also describe other cases of unrest both there and elsewhere in the wake of major price shocks. Our findings also have implications for future price movements. In Section 6, we combine our results with leading forecasts of future grain prices to estimate the projected change in conflict from 2010-2050. We predict that the effects of rising global demand coupled with the supply-side impact of climate change will contribute to an average increase in factor conflict by 12% and output conflict by 59%. More than half of the overall change can be attributed to the effects of climate change alone.

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. In Section 6, we discuss the magnitude of our results and conclude.

[3] Harari and La Ferrara (2014) and Bazzi and Blattman (2014), amongst many others, operate as dependent variables different types of violence either as sensitivity tests or in order to shed light on potential channels of causation. The examples most similar in spirit to our approach are Besley and Persson (2011), who make the case theoretically and empirically that states of one-sided violence and two-sided violence can be ordered (although their shock variables affect each in a similar way), and Dube and Vargas (2013), who show that while coffee price shocks and oil price shocks respectively affect each of their four main measures of violence similarly (that is, negatively for coffee and positively for oil), coffee price shocks have no significant impact on paramilitary political kidnappings, while oil price shocks have a significantly positive effect. This suggests that paramilitary political kidnappings in Colombia is associated with the predation motive—perhaps as a tool for extortion—but not with the type of violence driven by the the opportunity cost motive.

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. We define producers as unitary subnational polities that control rents from landownership. Building on Chassang and Padro i Miquel (2009), these groups solve a dynamic problem in which they can either (i) farm peacefully in the productive sector; or (ii) launch armed attacks to acquire territory through the technology of factor conflict. Consumers are atomistic agents who make decisions on whether to (i) provide wage labor in the productive sector; (ii) appropriate producer surplus through the technology of output conflict; or (iii) provide wage labor to an armed factor conflict group. Our goal is to examine the effect of food prices on these decisions.

Consider two producer groups $g \in \{1, 2\}$ sharing territory of size N. Land is used to produce crops. Group income in period t is generated according to:

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

where $\mathbf{N}_g = [N_{g1}, N_{g2} \dots N_{gn}]$ is the area of land that group g controls and N_{gj} is the share of $\mathbf{N}_g$ used to produce crop j; $\mathbf{P_t} = [P_{1t}, P_{2t} \dots P_{nt}]$ is a vector of crop prices in period t; and $\mathbf{P_t} \cdot \mathbf{N}_g = \sum_{j=1}^{n} P_{tj} N_{gj}$. The amount of group g's labor used for production is l_{gt}. Each group controls $\frac{1}{2}$ units of labor, implying that $l_{1t} + l_{2t} = L \in (0, 1)$. 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:

$$U_g = \sum_{t=1}^{\infty} \delta^t Y_{gt},$$

where Y_{gt} is group g 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.[4] Hence, the expected value of Y is well defined as $\mathbb{E}(Y) = \bar{Y}$.

Individual consumers are defined as net suppliers of labor and net demanders of crop output. Each consumer i maximizes utility by choosing an optimal crop bundle $\mathbf{x_i}$, subject to crop prices and a wage rate w per individual unit of work. There are no other sources of income, and consumers spend all of their wages on food. Consumer preferences are represented by an increasing and strictly quasi-concave utility function $U_i(\mathbf{x})$. The maximization problem is as follows:

[4] 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.

$$V_i(\mathbf{P}, w) = \max_{\mathbf{x}} U_i(\mathbf{x}), \quad \text{s.t.} \quad \mathbf{P} \cdot \mathbf{x_i} = w \tag{1}$$

We assume that property rights are not perfectly protected—a reasonable assumption in rural areas of many African countries. This feature permits producers to consider appropriating territory, and consumers to consider appropriating output.

2.1 Producer decision

As an alternative to productive activities, groups can try to seize land by violent means. 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.

Groups begin 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 $\frac{N}{2}$.

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:

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

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:

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

Rearranging, peace is possible if:

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

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:

$$V^P = \mathbb{E}\left[\sum_{t=1}^{\infty} \delta^t \mathbf{P_t} \cdot \frac{\mathbf{N}}{2}\right] = \frac{\bar{\mathbf{P}} \cdot \frac{\mathbf{N}}{2}}{(1-\delta)} \equiv \frac{\bar{Y}}{2(1-\delta)}, \tag{3}$$

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:

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

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 (2) 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

$$1 - 2\pi(1 - v) > 0. \tag{4}$$

Note, however, that it is not a sufficient condition. As the right hand side of (2) is strictly positive, there must exist a $\mathbf{P_t}$ close enough to 0 such that conflict is inevitable, even if (4) 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. This is generated by the transitory nature of price shocks: a drop in prices will have a comparatively weak effect on the present value of victory (permanent control of land) relative to the opportunity cost of fighting (lost income from farming in time t).[5] This feature generates our prediction: higher realizations of $\mathbf{P_t}$ will reduce the probability of observing factor conflict events in an agricultural area.

2.2 Consumer decision

As an alternative to providing wage labor in the productive sector, consumers can directly appropriate producers' surplus through the technology of output conflict.[6] Drawing on Dal Bó and Dal Bó (2011), we denote by L_Q the share of labor in this 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. The total amount of appropriated production is therefore $Q(L_Q)[\mathbf{P} \cdot \mathbf{N}]L$.

A consumer's decision to appropriate is one that satisfies the following condition:

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

where the left hand side represents the individual payoff from appropriation, given by the value of appropriated goods per individual unit of labor allocated to that sector, and right hand side is the payoff from one of unit of productive work net of appropriation. A consumer will appropriate as long as it is profitable to do so. The equilibrium level of appropriation will be reached when the terms in (5) are equated.[7]

Our goal is to determine how shocks to crop prices will affect this equilibrium. 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 staple "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 staple "import crops": crops that are consumed in a given cell but produced elsewhere. We consider two main mechanisms:: (i) a *predation* effect, in which higher prices increase the value of appropriable surplus; and (ii) an *income* effect, in which higher prices decrease real wages.

Denoting by $\mathbb{A}$ the left hand side of (5), and by $\mathbb{W}$ the right hand side adjusted for purchasing power, i.e. $\mathbb{W} = [1 - Q(L_Q)]\frac{w}{P_{j\in\{f,m\}}}$, the equilibrium level of appropriation will increase if the price shock raises the marginal consumer's payoff from appropriation more than it raises the payoff from productive labor, or: $V'_{iA}(P_j, w) - V'_{iW}(P_j, w) > 0$.

[5]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.

[6]We consider the third option of joining armed factor conflict groups below

[7]Dal Bó and Dal Bó (2011) discuss the existence of an equilibrium with positive levels of conflict in a similar set up. In our case, we can rewrite the equilibrium condition as $Q(L_Q) = \frac{w}{rN+wL}L_Q$ by substituting $rN + wL$ for $\mathbf{P} \cdot \mathbf{N}$. If $Q(0) = 0$ and $Q'(0) > \frac{w}{rN+wL}$, there is an equilibrium with positive $Q(L_Q)$ determined by the intersection of $Q(L_Q)$ with $\frac{w}{rN+wL}L_Q$. This is due to the concavity assumption in $Q(L_Q)$ caused by congestion effects. These conditions ensure that $L_Q \in (0, 1)$.

Food crops We begin by examining a change to P_f, the price of staple food crops that are both produced and consumed in a given cell. We first make the simple observation that

$$\frac{\mathrm{d}\mathbb{A}}{\mathrm{d}P_f} = \frac{Q(L_Q)N_f L}{L_Q} > 0. \tag{6}$$

Higher food crop prices increase the payoff from appropriation, or $V'_{iA}(P_f, w) > 0$.

In determining the sign of $V'_{iW}(P_f, w)$, the effect of a change in P_f on the value of productive labor, we must take into account both the direct effect of the price change on consumption as well as any potential induced wage response, as in Ravallion (1990).[8] Doing this, we can say that $V'_{iW}(P_f, w) \leq 0$ if:

$$\mathrm{d}P_f x \geq [1 - Q(L_Q)]\mathrm{d}w, \tag{7}$$

which can be rewritten in the following form:

$$\frac{P_f x}{w[1 - Q(L_Q)]} \equiv 1 \geq \eta, \tag{8}$$

where $\eta = \frac{\mathrm{d}w}{\mathrm{d}P_f}\frac{P_f}{w}$, the elasticity of the wage rate to the price of food.

Proposition 2. $V'_{iA}(P_f, w) - V'_{iW}(P_f, w) > 0$ *if* $\frac{P_f x}{w[1-Q(L_Q)]} \equiv 1 \geq \eta$. *An increase in food prices* P_f *will raise the equilibrium level of output conflict as long as the elasticity of the wage rate to* P_f *is not greater than unity.*

The proof comes from (6), which implies that $V'_{iA}(P_f, w) > 0$, and (8), which, if it holds, implies that $V'_{iW}(P_f, w) \leq 0$. The intuition is straightforward: higher food prices increase the value of appropriable output (generating a predation effect), while simultaneously decreasing the real wage of laborers (generating an income effect), as long as the induced wage response does not reverse the erosion of purchasing power caused by the increase in prices. These combined effects increase the profitability of appropriation relative to productive wage labor for the marginal consumer. As a result, equilibrium output conflict increases.

The critical value of unity in (8) is determined by the ratio of food expenses to wage income, which is unity by assumption in (1). In theory, η could be anywhere from 0 (de Janvry and Subbarao, 1984, 1986) to close to unity (Sah and Stiglitz, 1987). Studying the effects of rice price in Bangladesh, Ravallion (1990) estimates an η of 0.22 in the short run and 0.47 in the long run. One reason for the lag is that producers cannot expand production optimally in the time it takes for prices to pass through. A more relevant study in our context is by Ivanic et al. (2012), who estimate an average value of η of 0.42 for a comprehensive range of food crops in Africa.[9]

[8] We make the assumption that agents cannot substitute away from consuming staple food crops in the short run. Chen and Ravallion (2004), Ivanic and Martin (2008), and Ivanic et al. (2012) similarly ignore second order behavioral responses to staple food price shocks, as demand elasticities are low and the scope for substituting away from staples is diminished further when prices move together, as they did in 1996, 2005-2008, and, to a lesser extent, 2011 (see the middle panel of Fig. 2).

[9] These values of η are consistent with the estimated welfare effects of price spikes on poverty in rural areas of

These estimates for η imply that Proposition 2 holds even if we relax our assumption that consumers spend all of their earned income on food. For example, we can easily accommodate Haushofer and Shapiro's (2013) estimate of an elasticity of food expenditure to income of around 0.83 in Kenya. More generally, we can say from (8) that an increase in P_f will raise the equilibrium level of output conflict as long as the ratio of food expenditure to wage income for the marginal consumer is greater than or equal to the elasticity of the wage rate to P_f.

Cash crops We now examine a change to P_c, the price of cash crops that are produced in a given cell but consumed elsewhere. The critical difference between this case and the previous one is that there is no erosion of purchasing power when P_c rises; there is only a potential induced wage effect.

As before, $V'_{iA}(P_c, w) > 0$:

$$\frac{\mathrm{d}\mathbb{A}}{\mathrm{d}P_c} = \frac{Q(L_Q)N_cL}{L_Q} > 0. \tag{9}$$

A rise in P_c increases the value of appropriable surplus. However, provided that is a positive induced wage response ($\frac{\mathrm{d}w}{\mathrm{d}P_c} > 0$), it is also the case that $V'_{iW}(P_c, w) > 0$. It is therefore not possible to sign the effect of a change to P_c on equilibrium output conflict $[V'_{iA}(P_c, w) - V'_{iW}(P_c, w)]$, although we can say with confidence that this impact will be lower than the equivalent comparative static with respect to the food crop price.

Corollary 1. $[V'_{iA}(P_f, w) - V'_{iW}(P_f, w)] > [V'_{iA}(P_c, w) - V'_{iW}(P_c, w)]$ *if* $\frac{P_f x}{w[1-Q(L_Q)]} \equiv 1 \geq \eta$ *and* $\frac{dw}{dP_c} > 0$. *The effect of a change to* P_f *on equilibrium output conflict is greater than the effect of a change to* P_c *on equilibrium output conflict, as long as (i) the elasticity of the wage rate to* P_f *is not greater than unity; and (ii) the elasticity of the wage rate to* P_c *is greater than zero.*

All else equal, $V'_{iA}(P_f, w) = V'_{iA}(P_c, w)$ from (6) and (9). If the elasticity of the wage rate to P_c is greater than zero, then $V'_{iW}(P_c, w) > 0$. We show in Proposition 2 that $V'_{iW}(P_f, w) \leq 0$ if the elasticity of the wage rate to P_f is not greater than unity.

The results comes from the critical difference between P_f and P_c: agents consume food crops, but not cash crops. In both cases, higher prices increase the value of appropriable output, generating a predation effect. However, higher food crop prices lower the real returns to productive labor under the conditions described above, generating an income effect and making appropriation more attractive at the margin; but higher cash crop prices *increase* the real returns to productive labor as long as there is an induced wage effect.

Import crops and output conflict Finally, we examine a change to P_m, the price of staple food crops that are consumed in a given cell but produced elsewhere. By definition, import crop

developing regions. For example, Ivanic and Martin (2008) examine the overall impact of the 2005-2007 food price spike on the $1 per day poverty rate in eight developing countries. In rural parts alone, they estimate that the poverty rate increased by 0.4 percentage points when the wage response is not taken into account, and by 0.3 when it is. This net effect is significantly larger for the three African countries in their sample: 0.5 percentage points for Malawi, 1.1 for Zambia, and 1.4 for Madagascar. This is gross of the impact on landowners, and so can be considered a lower bound for the impact on farm workers that we consider here. In the short run, at least, farm wages in developing countries do appear to capture increases in commodity prices.

prices only affect conflict in net consumer cells. The real value of the productive sector wage $\mathbb{W}$ is the nominal wage deflated by P_m. As crop m is not produced domestically, (i) there is no induced wage effect; and (ii) we adjust the spoils of appropriation $\mathbb{A}$ by replacing the value of production $P_j N_j$ with the value of the stock of imported staple food $P_m \bar{M}$. It follows that:

$$\mathbb{A}_m = \frac{Q(L_Q) P_m \bar{M} L}{L_Q} \Rightarrow \frac{\mathrm{d}\mathbb{A}_m}{\mathrm{d}P_m} = \frac{Q(L_Q)\bar{M} L}{L_Q} > \frac{\mathrm{d}\mathbb{W}}{\mathrm{d}P_m} < 0 \tag{10}$$

Proposition 3. $V'_{A_m}(P_m, w) - V'_W(P_m, w) > 0$. *An increase in imported food prices P_m raises the equilibrium level of output conflict.*

A change to P_m raises the value of food stocks in a net consumer cell, while simultaneously reducing the real value of wages in the productive sector. This will induce consumers to appropriate rather than work until congestion effects ensure that the marginal value of appropriation returns to the equilibrium state $\mathbb{A}_m = \mathbb{W}$.

Import crops and factor conflict Proposition 1 implies that higher values of P_f and P_c reduce the likelihood of factor conflict. However, this logic clearly does not extend to P_m, the price of crops that are consumed in a given cell but produced elsewhere. Here, we consider the conditions under which a rise in P_m affects a consumer's decision to provide labor to an armed group.

Let armed groups optimally determine whether or not to launch attacks in net consumer cells.[10] In the absence of a battle, consumers simply solve $\max_{k \in \{\mathbb{W}, \mathbb{A}_m\}} V_{ik}$ as above, where k denotes the choice between alternatives. In the presence of a battle, armed groups determine their optimal quantity of labor, and the consumer's choice set extends to $k \in \{\mathbb{W}, \mathbb{A}_m, \mathbb{F}\}$, where $\mathbb{F}$ is the payoff from fighting with an armed group. Fighting involves the risk of fatality or major physical harm. Let λ_i represent consumer i's probability of surviving a battle without major harm; with probability $1-\lambda_i$, consumers receive a payoff of zero.[11] We can express the expected utility of fighting as follows:

$$\mathbb{E}\big[V_{i\mathbb{F}}(P_m, w^f, \lambda_i)\big] = \lambda_i V_i(P_m, w^f), \tag{11}$$

where w^f is the wage rate offered by armed groups, and $\lambda_i \in [0, 1)$. Note that $w^f > w$, otherwise the expected physical cost of fighting will ensure that consumers always prefer to work in the productive sector. Also note that λ_i varies across consumers; some are more likely to suffer physical harm than others. Consumer i will therefore join the armed group if:

$$\lambda_i > \frac{\max_{k \in \{\mathbb{W}, \mathbb{A}_m\}} V_{ik}(P_m, w)}{V_i(P_m, w^f)}. \tag{12}$$

To determine the effect of a change to P_m on this decision, we must make further assumptions about consumer preferences. Consider an additional constraint on food consumption such that $x > \underline{x_i}$; consumption must meet a minimum caloric intake larger than $\underline{x_i}$.[12] If $x \leq \underline{x_i}$, utility is

[10] E.g., in our illustration from Côte d'Ivoire below, this decision is triggered by a disputed election.
[11] This could represent fatality or an erosion of earning ability.
[12] This is consistent with a simplified Stone-Geary utility function of the form $u_i = x - \underline{x_i}$.

zero. Furthermore, denote by P^{γ}_{mi} the price of food that prevents the consumer i with wage income w from consuming $x > \underline{x_i}$. That is, $V(P^{\gamma}_{mi}, w) = 0$.

This subsistence requirement imposes a natural limit on consumers' ability to substitute staple food consumption intertemporally. It follows that, in order to maintain an essential level of food consumption in the wake of sufficiently large price shocks, consumers will require access to some form of savings, credit, or insurance. Absent these smoothing mechanisms, they must resort instead to costly coping strategies (Chetty and Looney, 2006).

Proposition 4. *For consumers with a minimum consumption requirement $x > \underline{x_i}$ and without access to conventional smoothing mechanisms:*

$$P_{mt} = P^{\gamma}_{mi} \Rightarrow Pr(x > \underline{x_i} \mid k_i = \mathbb{F}) \geq Pr(x > \underline{x_i} \mid k_i = \{\mathbb{W}, \mathbb{A}_m\}) = 0.$$

If import food prices are at the critical value P^{γ}_{mi}, then consumer i will receive their minimum consumption requirement $\underline{x_i}$ with a weakly positive probability when they choose $k_i = \mathbb{F}$, and with a probability of 0 when they choose $k_i = \{\mathbb{W}, \mathbb{A}_m\}$.

The right hand side is zero by definition only after congestion effects ensure that the payoff from output conflict returns to the equilibrium state $\mathbb{A}_m = \mathbb{W}$. To that extent, this proposition is true in the long run only. The left hand side is zero if $\lambda_i = 0$ (from (11)), and positive if $\lambda_i > 0$, as $x_i(w^f, P^{\gamma}_{mi}) > \underline{x_i}(w, p^{\gamma}_{mi})$.

These are the conditions under which we expect higher food prices lead to factor conflict in net consumer cells. A sufficiently large negative income shock—in the form of high food prices—causes some consumers to fall below the margin of a minimum consumption target $\underline{x_i}$, and consequently to undertake the risk of joining an armed group in order to consume $\underline{x_i}$ with a positive probability, provided that $\lambda_i > 0$.

Empirical evidence suggests that the main assumptions underlying these results are plausible. First, Ivanic et al. (2012) estimate that the 2010-2011 food price shock pulled 68 million net consumers in less developed countries beneath the \$1.25 per day extreme poverty line, while also lifting 24 million producers above it.[13] Applying the same ratio of producer and consumer effects to the overall effects reported in Ivanic and Martin (2008), we estimate that the 2005-2007 price surge pulled an estimated 162 million consumers beneath the extreme poverty line.[14] Taken together, these findings support the notion that a critical price P^{γ}_{mi} exists and is relevant for the poorest consumers in our sample. Second, they also indicate that millions did not have sufficient access to conventional consumption smoothing mechanisms, which is consistent with the correlated nature of the real income shock caused by food prices. Finally, the idea that poor households must engage in risky or costly coping behavior in the face of such shocks is in keeping with evidence from a broad

[13]Dollars are PPP-adjusted

[14]This is derived from a 9-country sample, in which they estimate that, net of producer effects, the price shock increased the poverty rate by 2.7 percentage points; for the African countries in the sample, this ranged from 3.6 to 4.9 percentage points.

empirical literature (e.g., de Janvry et al., 2006; Dupas and Robinson, 2012; Miguel, 2005; Oster, 2004).

2.3 Discussion

Table 1 summarizes the main theoretical predictions.[15]

1. In food-producing cells, higher prices *reduce* factor conflict, as rural groups choose to farm rather than to attack neighboring territory.
2. In food-producing cells, higher prices *increase* output conflict, as net consumers appropriate increasingly valuable output while their real wages fall.
3. In food-consuming cells, higher prices *increase* output conflict, as net consumers appropriate increasingly valuable stock while their real wages fall.
4. In food-consuming cells, higher prices *increase* factor conflict, as consumers at the margin of a target consumption level are more likely to join armed groups in conflict zones.

Table 1: Theoretical predictions

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

While it is not possible to assign a single cause to a particular conflict episode, it is nevertheless illustrative to briefly consider recent cases of conflict within our sample countries in light of the model's predictions. The First (2002-2005) and Second (2011) Ivorian Civil Wars represent particularly relevant examples of factor conflict in the wake of significant price shocks. Côte d'Ivoire was largely stable under the rule of Felix Houphouet-Boigny since its independence from France in 1960. Following his death in 1993, escalating sectarian tensions precipitated a period of political instability, which culminated in the outbreak of civil war in 2002 between the largely Muslim supporters of Alesanne Ouattara in the north and President Laurent Gbagbo's Christian supporters in the south. By the end of the violence in 2007, approximately 1370 lives were lost (Sundberg and Melander, 2013).

The Ivorian economy relies heavily on cocoa and coffee exports. The case literature suggests the decline of these export commodity prices throughout the 1980s and into the 1990s led to the rise of

[15] We omit Corollary 1, 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 at least equal to the value of output that would be contested.

ethno-religious tensions and more competition for land (Woods, 2003; Wong, 2005; Economic and Political Weekly, 2004). Woods (2003, p. 648) notes that:

> As [...] incomes from cocoa exports declined, pressures to control access to land rose. It was within this context that the issue of citizenship came to the fore. At the national level, defining who was a citizen and who was not became central to excluding certain individuals from competing in national elections. At the village level, competition and conflict surfaced over land, along with growing calls by those who saw themselves as 'indigenous' to restrict the rights of foreigners to acquire land and to vote.

It is interesting in the context of Proposition 1 to note that these tensions spilled over into outright civil war only after cocoa and coffee prices fell to historical low points in 2000 and 2001 respectively, dragging the Ivorian economy into recession with consecutive GDP per capita growth rates of −4.34% and −1.96%.[16] Amid the larger scale contest for central political control, examples of village-level "micro-conflicts" over land across the cocoa belt were picked up by international media outlets, depicting for the most part violence arising from the expulsion of so-called foreigners from productive land by self-styled "indigenous" southerners.[17] The violence ceased by 2005 and a peace deal was signed in 2007, by which time both cocoa and coffee prices had recovered.

The Second Ivorian Civil War broke out in March 2011 after Gbagbo refused to concede the 2010 presidential election, despite both the country's Independent Electoral Commission and the international community acknowledging Outtara as the true victor.[18] This was one of 63 elections in Sub-Saharan Africa from 1990-2012 that is deemed to have exhibited irregularities by the African Elections Database.[19] However, it is one of a handful that escalated into a full-blown civil war, which ultimately left more than 3,000 civilians dead.[20] It concluded with the Battle of Abidjan—the country's commercial capital—and the arrest of Gbagbo by French, UN and Ouattara-aligned forces. "'

In contrast to the first civil war, this conflict began as cocoa and coffee prices hovered near record highs. Again unlike a decade earlier, prices for staple food crops—among the country's main imports—were also approaching record peaks. Our model (Proposition 4) indicates that the poverty caused by these staple food price shocks incentivized some net consumers to join the armed conflict for a sufficiently high wage. In that light, it makes sense that only 3 out of 22 battles (13.6%) in the second civil war took place outside of urban areas, as compared to 19 out

[16] World Bank, accessed August 25 2017 at: https://data.worldbank.org/indicator/NY.GDP.PCAP.KD.ZG?cid=GPD_31&locations=CI.

[17] See, for example, "Chocolate war erupts in Ivory Coast," *The Guardian*, May 13 2004, accessed August 25 2017 at: https://www.theguardian.com/world/2004/may/14/rorycarroll; "Land Quarrels Unsettle Ivory Coast's Cocoa Belt," *The New York Times*, May 26 2004, accessed August 25 2017 at: http://www.nytimes.com/2004/05/26/world/land-quarrels-unsettle-ivory-coast-s-cocoa-belt.html; and "Three killed in Ivory Coast land dispute", *Reuters*, May 8 2001 (Sundberg and Melander, 2013).

[18] "Ivory Coast: death squads on the rise as civil war looms," *The Guardian*, December 22 2010, accessed August 25 2017 at: https://www.theguardian.com/world/2010/dec/22/ivory-coast-death-squads.

[19] For more information on this dataset, see http://africanelections.tripod.com/about.html.

[20] This figure comes from Human Rights Watch, accessed August 28 2017 at https://www.hrw.org/report/2011/10/05/they-killed-them-it-was-nothing/need-justice-cote-divoires-post-election-crimes.

of 52 (36.5%) in the first (Raleigh et al., 2010). Moreover, the conflict's end followed a wave of defections by Gbagbo's troops as Ouattara's Republican Forces made advances across the country. Reports suggest that these defections were rooted in Gbagbo's inability to pay sufficient wages, owing in part to the role of international sanctions.[21]

Finally, it was widely reported that Liberian mercenaries fought in large numbers for Gbagbo, and perhaps even for Ouattara.[22] In a survey of former Liberian Civil War combatants conducted at the time of the Ivorian crisis, Blattman and Annan (2016, p. 2) found that 3-10% of respondents reported actions such as attending secret meetings with recruiters or being willing to fight in Côte d'Ivoire "at the going recruitment fees." However, in a randomly selected subsample treated with agricultural training, capital inputs and counseling, ex-combatants were around a quarter less likely to report these mercenary recruitment activities. The program increased their incomes by around $12 per month, and had little effect on peer networks, social integration, or attitudes toward violence. The study indicates not only that economic motives were a significant driver of this particular conflict, but that the cross-price elasticity of labor supply between peaceful and illicit sectors more generally is substantial, as potential fighters are highly responsive to small changes in relative wages. This is a critical assumption throughout our model.[23]

With respect to output conflict, examples of incidents plausibly linked to the food price spikes of 2008 and 2010/11 are plentiful. For example, in a single article, Reuters reported recent "price rise protests and disturbances" in in 15 countries, 8 of which were African.[24] In some cases demonstrations led to policy changes aimed at lowering food prices (e.g., Cameroon, Mozambique), in others they involved direct looting (e.g., Burkina Faso).[25] Examples of both can be found in Côte d'Ivoire, where, in 2008, then-President Gbagbo cancelled custom duties after two days of violent protests in Abidjan;[26] and, during the 2011 shock, a UN Refugee Agency warehouse was looted in the agricultural market town of Guiglo (Raleigh et al., 2010).[27]

Examples elsewhere also evoke direct connections to our model. For example, in a rural part of the Kopsiro Division in the Mount Elgon District, Kenya, a town was raided "for food supplies on several occasions" during the 2008 price shock. In the Bari region of Somalia, food was stolen from

[21] "Ivory Coast Battle Nears Decisive Stage in Key City," *The New York Times*, March 31 2011, accessed August 28 2017 at: http://www.nytimes.com/2011/04/01/world/africa/01ivory.html.

[22] For example, see "Liberia Uneasily Linked to Ivory Coast Conflict," *The New York Times*, March 31 2011, accessed August 28 2017 at: http://www.nytimes.com/2011/04/01/world/africa/01liberia.html.

[23] Dube et al. (2016) also provide evidence in support of this by showing that lower maize prices in Mexico led to households planting more drug crops and, ultimately, to more drug-related killings.

[24] "Food price rise sparks protests," *Reuters*, May 15 2008, accessed August 28 at: http://www.reuters.com/article/us-food-prices-protests-idUSL1579452720080515.

[25] These policy changes suggest that one motive for consumers in urban areas is to provoke government actions that will lower food prices. To the extent that these protests imply both an opportunity cost in terms of time and an expected benefit in terms of lower food prices, we can interpret them as a variant of the behavior predicted by Proposition 3. In our empirical analysis, we attempt to separate these urban "policy protests" from the predatory output conflict more explicitly defined in our model.

[26] "Riots prompt Ivory Coast tax cuts," *BBC News*, April 2 2008, accessed August 28 2017 at: http://news.bbc.co.uk/1/hi/world/africa/7325733.stm.

[27] These typically contain supplies of staple cereals; see https://emergency.unhcr.org/entry/86993/warehouse-space-standards.

a World Food Program truck by "nomadic armed men", who distributed it to "nomad families who complain that they are not targeted by food aid" during the 2011 shock. Also in Somalia, 25 megatons of assorted food commodities were looted from a storage facility in Bacad Weyne, a rural town near the Ethiopian border in the Mudug region. These are among many examples documented in the ACLED dataset (Raleigh et al., 2010), described in more detail below.

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 × 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 A3.

3.2 Conflict

Main factor conflict measure: *UCDP Factor Conflict* Our theory requires 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.[28] 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.[29] 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.[30]

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%,

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

[29] 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.

[30] 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; *"Scores feared dead as Nigerian villagers battle over farmland"*. AFP, 4/25/2005; *"Tension runs high in west Ivory Coast cocoa belt. [20 killed.]"* Reuters, 11/14/2002; *"Five killed as tribes battle over land in Kenya's Rift Valley region."* AFP, 2/13/2006; *"Tribes in Chad feud over land around well, 50 dead."* Reuters, 11/23/2000.

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.[31]

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 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%.[32]

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 67,000 responses across 19 countries to questions on whether or not individuals experienced theft or violence in the preceding year. The data are collected as repeated cross-sections between 1999 and 2009. In Table 2, we see that over 30% of respondents report having experienced theft in the

[31] In robustness tests, we also operate an alternative measure of factor conflict from the ACLED dataset. It records conflicts after which (non-state) armed groups gain control of territory. This has the advantage of including only battles that align with our definition of factor conflict; the disadvantage is that is likely to be a small subset: the unconditional probability of observing this event is 0.4%.

[32] 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)

past year, while 13% have been victims of violence.[33] 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. We discuss this dataset in more detail in Section 5.3.

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.

3.3 Prices

To study the causal effect of price variation on conflict, we require price data with three general properties: sufficient 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

[33] 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?"*

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, year fixed fixed effects, country time-trends, weather conditions, oil prices, and mineral 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 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. As we write above, Ivanic et al. (2012) evaluate the effect of the 2010-11 price change for 38 commodities on extreme poverty in 28 countries, finding that the shock pulled 68 million net consumers below the World Bank extreme poverty line of $1.25, while pushing 24 million 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. For cell i, country c and year t the price index is given by

$$PPI_{ict} = \sum_{j=1}^{n} (P_{jt} \times \underbrace{N_{jic}}_{crop\ share\ of\ land}) \tag{13}$$

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. Global crop prices are taken from the IMF *International Finance Statistics* series and the World Bank *Global Economic Monitor* and are each indexed at 100 in the year 2000.[34] In addition to this aggregated index, we also compute disag-

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

gregated 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 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.[35] 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:

$$CPI_{ct} = \sum_{j=1}^{n} (P_{jt} \times \underbrace{\Theta_{jc}}_{crop\ share\ of\ calories}) \tag{14}$$

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 cell-level *Population* (which we extrapolate from five year intervals to form a cell-year estimate) and *Distance to city* (measured in 100km units).[36] *Luminosity* is a dummy variable indicating whether or not light density within cells is visible from satellite images taken at night. We include statistics from 1992 (the earliest year for which data are available) and 2010. 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. The data come from the National Oceanic and Atmospheric Administration (NOAA) Defense Meteorological Satellite Program's Operational

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

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

Linescan System that reports images of the earth at night captured from 20:30 to 22:00 local time.[37]

4 Estimation framework

Factor conflict To estimate the impact of producer and consumer food prices on factor conflict, we propose the following specifications:

$$\begin{aligned} factor\ conflict_{ict} &= \alpha_i + \sum_{k=0}^{2} \beta^p_{t-k} PPI_{ict-k} + \gamma_{ct} + \epsilon_{ict} \\ factor\ conflict_{ict} &= \alpha_i + \sum_{k=0}^{2} \beta^p_{t-k} PPI_{ict-k} + \sum_{k=0}^{2} \beta^m_{t-k} CPI_{ct-k} + \gamma_c \times trend_t + \epsilon_{ict} \end{aligned} \tag{15}$$

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; γ_{ct} is country $\times$ year fixed effects; $\gamma_c \times trend_t$ is a country-specific time trend; and ϵ_{ict} is the error term. We report two standard errors for each coefficient: one that is corrected for spatial and serial correlation within a radius of 500km, using the procedure developed by Conley (1999) and implemented by Hsiang (2010); and one that is corrected for spatial correlation across countries and serial correlation within cells, which is generally more conservative.[38] 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 in any case. 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 Propositions 1 and 4 respectively, we expect that β^p is negative and β^m is positive when the outcome is factor conflict incidence or onset, and the reverse when the outcome is factor conflict offset.

In the first specification, β^p is estimated off within-country-year variation in prices and conflict. The cost to this approach is that we cannot include the CPI, which varies at the level of a country-year.[39] In the second specification, we include the CPI and substitute the country-year trend for country $\times$ year fixed effects. The identifying assumption is that, after accounting for time-invariant factors at the cell level and common trending factors at the country level, variation in the consumer and producer price indices is not correlated with unobserved factors that also affect conflict. While we argue that this assumption is plausible, we report in the Appendix specifications that also

[37] Accessed at https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html on July 1st, 2017. (see Michalopoulos and Papaioannou, 2013, for a discussion on the particular suitability of nighttime lights as measure for economic development in Africa).

[38] We show in the Appendix that our main results are robust to setting the Conley standard error distance cutoff from 100km to 1000km (in intervals of 100km).

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

include cell-level controls for an oil price index, a mineral price index, and various weather controls as well as year fixed effects. We favor our estimate for β^m without year fixed effects, as most of the variation in the CPI is over time rather than across countries (i.e., there is more spatial homogeneity in food consumption than in crop production).

Output conflict To estimate the impact of producer and consumer food prices on output conflict, we propose the following specifications:

$$\begin{aligned} output\ conflict_{ict} &= \alpha_i + \sum_{k=0}^{2} \theta^p_{t-k} PPI_{ict-k} + \gamma_{ct} + e_{ict} \\ output\ conflict_{ict} &= \alpha_i + \sum_{k=0}^{2} \theta^p_{t-k} PPI_{ict-k} + \sum_{k=0}^{2} \theta^m_{t-k} CPI_{ct-k} + \gamma_c \times trend_t + e_{ict} \\ output\ conflict_{ict} &= \alpha_i + \sum_{k=0}^{2} \theta^{pf}_{t-k} PPI^{food}_{ict-k} + \sum_{k=0}^{2} \theta^{pc}_{t-k} PPI^{cash}_{ict-k} + \gamma_{ct} + e_{ict} \end{aligned} \tag{16}$$

The first two are analogous to the specifications in (15), only with output conflict as the outcome variable in this case. The critical difference is that we expect both θ^p and θ^m to be positive, as predicted in Propositions 2 and 3.

The third specification provides a test of Corollary 1. PPI^{food} is the 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, and rice. The PPI^{cash} component picks up the remaining cash crops such as coffee, tea and tobacco (capturing P_c from the model). We expect that $\theta^{pf} > 0$ and $\theta^{pf} > \theta^{pc}$.

5 Results

5.1 Factor conflict

Main results In Table 3, we present results from the specifications in (15) for conflict incidence, onset and offset. In all regression tables, coefficients represent the cumulative impact over three years of a one standard deviation rise in a given price index.[40]

Column (1) shows the result of a regression that omits the CPI and includes country × year fixed effects (CYFEs). A one standard deviation rise in the PPI decreases the incidence of factor conflict by 0.0042, or 15.4% of the mean. The estimate is significant at the 1% level with both Conley standard errors and two-way clustered standard errors. In Column (2), we include the CPI and replace CYFEs with a country-specific time trend. The PPI reduces conflict by 17.2% ($p < 0.01$), and the CPI increases conflict by 8.6%. The CPI effect has a p-value of 0.127 with

[40]We use the sample standard deviation over time, as it is more meaningful in the context of price shocks than the overall sample standard deviation that contains both temporal and spatial variation.

Conley standard errors, and 0.116 with two-way standard errors. In both cases, the PPI and CPI coefficients are significantly different from each other.

In Columns (3) and (4), we see similar results where factor conflict onset is the dependent variable. The PPI effects are -16.3% and -20% respectively, and are precisely estimated in both specifications. The CPI effect is $+10.2\%$, and is again significantly different from the PPI effect, but not significantly different from zero at the 10% level.

In Columns (5) and (6), we show that both indices significantly affect the duration of factor conflict. The PPI increases the probability that factor conflict will end by 8.3% and 9.2% respectively, and the CPI reduces it by 16.5% ($p < 0.01$). This is consistent with the idea in Proposition 4 that rising prices force low-income net consumers to join existing armed groups rather than launch new conflicts. Again, in both specifications the PPI and CPI effects are significantly different from each other.

The upper panel of Figure 4 presents visual output based on a variant of the specification estimated in Column (2). 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 support a linear treatment of the main effects.

Taken together, the main results indicate that rising food prices significantly reduce the onset and duration of factor conflict in food-producing cells, while significantly prolonging factor conflict in food-consuming cells. In all six specifications, the effects of the PPI and CPI are significantly different from each other.

Robustness In Appendix Section C.1, we examine the robustness of these main results to a variety of sensitivity tests. In Table A2, we cumulatively add (i) year fixed effects; (ii) cell-level weather covariates and oil prices $\times$ cell- and country-level production indicators; and (iii) mineral prices $\times$ cell-level mine indicators from Berman et al. (2017). The PPI and CPI coefficients are significantly different from each other in seven of the resulting nine regressions, and all 18 coefficients carry the proposed sign. The nine PPI estimates are significantly different from zero. The CPI estimates are generally noisier with year fixed effects, although the impact on conflict incidence is large and significant with the full set of controls, and estimates are either below or close to the 10% significance level in five specifications.

We also show that the results are qualitatively robust to recoding the outcome variable as "two-sided" conflict only (Table A3); varying the Conley standard error kernal cutoff from 100km to 1000km in increments of 100km (Table A4); aggregating the cell area to 1 degree cells (i.e., by a factor of four; Table A5); adding to that specification controls for the PPI in neighboring cells (Table A6); including a cell-year estimate of population as a control variable (Table A7); estimating a conditional fixed-effects logit model (Table A8); weighting the CPI and PPI components by the extent to which crops are traded by a given country (Table A9); weighting the PPI by crop yields per hectare (Table A10); and including contemporaneous price indices only (Table A11).

Heterogeneity Our model also provides guidance on a source of heterogeneity in the consumer price effect that we can test in the data. Recall the 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, setting variable equal to 1 if a grid cell showed non-zero luminosity in a given year. The impact of the CPI 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 PPI on factor conflict also ought to be closer to zero where $luminosity = 1$.

Introducing the luminosity variable allows us to estimate a variant of the equations in (15) that contains $CPI_{ct-k} \times luminosity_{ic}$, $PPI_{ict-k} \times luminosity_{ic}$ and country $\times$ year fixed effects, as the interaction generates variation in the CPI at the subnational level. To that end, this exercise serves as both a robustness exercise as well as a test of theoretical implications. Our model predicts that CPI interaction effect is negative.

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. Second, global price pass-through is likely to be larger in lit cells than in dark ones, as economic development may reflect more trade openness. This could lead us to falsely reject our prediction, as our model implies that economic development mutes the effect of prices on violence while the passthrough story implies the opposite. Third, it is plausible that conflict is more likely to occur in remote areas, where the state might lack the capacity to deter armed groups. In contrast to the passthrough mechanism, this could lead us to falsely corroborate our prediction, as remote cells are more likely to be dark.

To address the first concern, we include a cell-year measure of population in all specifications. To control for both price passthrough and remoteness/state capacity, we interact the following with the price indices: distance (in 100km units) to the next nearest lit cell; distance to the nearest port; distance to the nearest land border; and distance to the capital city.[41] The ex-ante sign of these interactions is unclear, given the tension between the competing mechanisms.

We use measures of luminosity taken at three different points: 1992 (the earliest available), 2000, and 2010. The 1992 measure comes at the end of a long period of stagnation in Africa, and fails to capture important economic gains of the 1990s and 2000s; on the other hand, it is less prone to capture endogenous responses to violence itself. We run two regressions with each measure: one

[41] Data on the distance from a cell to the nearest border and to the capital city are taken from the PRIO GRID dataset (Tollefsen et al., 2012). Distance to port is from the SEDAC project introduced above.

with a control for population (in addition to cell fixed effects and CYFEs), and one with additional controls for the four distance variables.

The results of this test are presented in Table 4. The outcome variable in each model is factor conflict incidence. In all six specifications, CPI $\times$ luminosity has a negative coefficient, and PPI $\times$ luminosity has a positive coefficient. Column (1) shows results from a model with luminosity measured in 1992. We see that the impact of a CPI shock in lit cells is -14.7% compared to dark cells, and that the estimate is significant with Conley standard errors but not with two-way clustered standard errors. In Column (2) we add the remaining covariates, which substantially mutes the impact. In Columns (3) to (6), however, we see that the CPI interaction is larger (in absolute terms) and more precisely estimated, ranging from -11% with the full set of controls to -22% without. Six of the eight p-values are below 0.05; the other two are 0.12 (2000 measure with full controls and two-way standard errors) and 0.22 (2010 measure with full controls and two-way standard errors).

Of the other covariates, it appears that the price passthrough effect is best captured by the distance to border variable, and to a lesser extent the distance to lights variable too. Distance to port, in the case of the CPI interaction at least, appears to capture the remoteness/state capacity effect instead. Distance to capital city has no moderating effect on the impact of either price index, conditional on the other covariates.

Taken together, these results support an implication of Proposition 4: the effect of consumer food price shocks on factor conflict is weaker in more economically developed cells. We also find a similar result with respect to producer prices. Economic development in both cases is proxied by nighttime luminosity from satellite images. This finding suggests that is it not only economic shocks that shape conflict, but also the interaction of shocks and levels.

5.2 Output conflict: ACLED

Main results In Table 5, we present results from the specifications in (16) for output conflict incidence, onset and offset. Again, in all regression tables, coefficients represent the cumulative impact over three years of a one (temporal) standard deviation rise in a given price index.

In Column (1), and in clear contrast to the case of factor conflict, we see that a one standard deviation rise in the PPI leads to an *increase* in the risk of output conflict of 15.1%. In Column (2), the PPI impact is 18.9%, while the CPI impact is 14.4%. All three estimates are significantly different from zero at the 1% level. In Columns (3) and (4), we see that both indices have large, positive and significant impacts on output conflict onset (55.7% and 22.9%). It is clear from Columns (5) and (6) that the main PPI effect is driven entirely by onset rather than offset, while the CPI has a consistently large effect on both onset and offset (-23.8%).

The lower panel of Figure 4 presents visual results from a regression of output conflict on the PPI, the CPI (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 presents results from the lower specification in (16), in which the producer price index is separated into food crops (*Producer Price Index: Food Crops*) and cash crops (*Producer Price Index: Cash Crops*) in order to test Corollary 1 by comparing the effects of P_f and P_c. A standard deviation rise in food crop prices increases the incidence of output conflict by 16.6% ($p < 0.01$), while the impact of cash crop prices is weakly negative. The estimates are significantly different from each other, corroborating the model's prediction. This is driven entirely by onset effects, as both offset impacts are close to zero and statistically indistinguishable.

Robustness In Appendix Table A12, we again cumulatively add (i) year fixed effects; (ii) cell-level weather covariates and oil prices $\times$ cell- and country-level production indicators; and (iii) mineral prices $\times$ cell-level mine indicators from Berman et al. (2017). As in the main results, the PPI effect is large, positive, and significant in incidence and onset regressions. The CPI effect is significant only in the offset regression with the full set of controls: a standard deviation rise in the CPI reduces the likelihood that output conflict ends by 57.3%. Otherwise, the inclusion of year fixed effects eliminates the CPI effect. In Table A13, we repeat the exercise without year fixed effects, finding that the CPI has the expected impact on incidence, onset, and offset without the mineral price controls, and on offset with the mineral controls. Taken together, the results indicate that the CPI effect on output conflict is mostly swept up by year fixed effects, but is large and robust in the presence of controls for temperature, precipitation, oil price indices and mineral price indices. This suggests that the CPI effect is largely a common shock across countries.[42]

We also show that the results are qualitatively robust to recoding the outcome variable as "riots" only (Table A14); varying the Conley standard error kernal cutoff from 100km to 1000km in increments of 100km (Table A15); aggregating the cell area to 1 degree cells (i.e., by a factor of four; Table A16); adding to that specification controls for the PPI in neighboring cells (Table A17); including a cell-year estimate of population as a control variable (Table A18); estimating a conditional fixed-effects logit model (Table A19); weighting the CPI and PPI components by the extent to which crops are traded by a given country (Table A20); weighting the PPI by crop yields per hectare (Table A21); and including contemporaneous price indices only (Table A22).

We also explore whether our measure of output conflict is picking up demonstrations 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), 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 plausibly be expected 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 A23 and are 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

[42] Although we note below that it is significantly larger in urban areas when we control for country $\times$ year fixed effects.

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 they are indistinguishable using the population-based measure. We conclude that our main output conflict results are not driven exclusively by urban protests designed to create unrest and agitate for policy reforms. This exercise has the additional benefit of introducing subnational spatial variation to the CPI, and showing that the interacted effect is significant in the presence of country $\times$ year fixed effects.

Finally, we investigate the possibility that the contrast we observe between the effects of PPI on factor conflict and output conflict are due to differences either in the study periods or in the data collection agencies, rather than due to the mechanisms put forward in our model. To hold the study period and data sources constant, we must either locate an output conflict measure in the UCDP dataset, or locate a factor conflict measure in the ACLED dataset. Given the restrictive criteria for conclusion in the UCDP dataset, we pursue the latter strategy. The challenge is to (i) identify large scale battles between armed groups over the control of territory in the broader ACLED dataset while (ii) ensuring that we do not pick up output conflict events, which would bias the PPI effect towards zero. In this light, the ACLED "Type 2" battle is suitable, as it records battles after which non-state armed groups overtake territory. The advantage is that it captures battles that fit our factor conflict definition, and ought to avoid incidents that fit our output conflict definition. The disadvantage is that the incidence of these battles is somewhat rare, with a mean of 0.41%.

Nevertheless, we proceed in Table A24 with a comparison between the main *UCDP Factor Conflict* measure, the *ACLED Territorial Change* alternative factor conflict measure, and the main *ACLED Output Conflict* measure. We present the results of two specifications for each outcome; the first with the largest possible sample (that is, 1989-2010 for UCDP and 1997-2013 for ACLED), and the second with the common overlap years only (1997-2010). The critical comparison is between the PPI coefficients in Columns (2), (4) and (6). With *UCDP Factor Conflict*, the effect is -18.5%; with *ACLED Territorial Change*, the effect is -15.0%; and with *ACLED Output Conflict*, the effect is $+8.9\%$. Moreover, the PPI and CPI effects are significantly different only in the factor conflict regressions, and not in the output conflict regression.

The results of this test indicate strongly that our distinction between the impact of PPI on factor and output conflict is neither an artifact of differences between the study periods nor the data sources.

5.3 Output conflict: Afrobarometer data

In this section, we incorporate data on interpersonal conflict from multiple rounds of the Afrobarometer household survey series. By merging our high resolution panel grid with survey data, we can pursue an alternative method of examining the relationship between food prices and output conflict. Specifically, we can identify whether or not farmers are more likely to experience theft or physical assault in the wake of a food price shock.

The Afrobarometer dataset consists of 86,804 observations collected in four rounds from 1999 to 2009 in 19 African countries. We geocode each observation at the level of a village (of which there are 6,186 with an average of 14.03 observations in each), and assign to it the attributes of the cell with the nearest centroid. Once we discard rounds that do not include critical variables for our main specification, we are left with slightly fewer than 40,000 observations.

Proposition (2) implies that higher food prices will cause net consumers to appropriate output in food-producing areas, and Corollary (1) implies that this effect will be positive and significant relative to the impact of higher cash crop prices in cash-crop-producing areas. From whom do they appropriate? In the model, we imply that output conflict 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 conflict, relaxing the assumption that output is traded only by producers at the farm gate. To measure output conflict at the micro level, we exploit two survey questions introduced in Section 3. Respectively, they ask how often respondents or their family members were victims of (i) theft or (ii) physical attack over the preceding year. We code them as binary variables, where 0 is never and 1 is at least once. These measures closely correspond to our theoretical concept of output conflict.

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 examine whether or not the effect of higher prices on theft/assault against commercial farmers in food-producing cells is larger than the equivalent effect against commercial farmers in cash-crop-producing cells. According to our model, output conflict rises with the PPI for food crops because the value of appropriable output increases while real wages *simultaneously decline*. By contrast, the PPI for cash crops raises 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, as follows:

$$\begin{aligned} victim_{jict} = \alpha_i &+ \sum_{k=0}^{n} \phi^{f}_{t-k} PPI^{food}_{ict-k} + \sum_{k=0}^{2} \phi^{c}_{t-k} PPI^{cash}_{ict-k} \\ &+ \sum_{k=0}^{n} \phi^{ff}_{t-k} PPI^{food}_{ict-k} \times farmer_{jict} + \sum_{k=0}^{n} \phi^{cf}_{t-k} PPI^{cash}_{ict-k} \times farmer_{jict} \\ &+ \sum_{k=0}^{n} \phi^{ft}_{t-k} PPI^{food}_{ict-k} \times trader_{jict} + \sum_{k=0}^{n} \phi^{ct}_{t-k} PPI^{cash}_{ict-k} \times trader_{jict} + \mathbb{X}'_{jict}\zeta + \gamma_{ct} + e_{jict}, \end{aligned} \tag{17}$$

where $victim_{ict}$ indicates whether or not an individual j in cell i, country c, and year t experienced theft or physical attack in the prior year; α_i is cell fixed effects; $farmer$ indicates that individual j is a commercial farmer, and $trader$ a trader, hawker or vendor; $\mathbb{X}$ is a vector of individual controls, including age, age squared, education level, gender, occupation ($farmer$, $trader$, or other) and urban or rural primary sampling unit; γ_{ct} are fixed effects for country $\times$ year; and e_{jict} is the error term, which we cluster by cell. Our treatment effects of interest for farmers and traders respectively are:

$$\sum_{k=0}^{n} \phi_{t-k}^{ff} - \sum_{k=0}^{n} \phi_{t-k}^{cf} \tag{18}$$

and

$$\sum_{k=0}^{n} \phi_{t-k}^{ft} - \sum_{k=0}^{n} \phi_{t-k}^{ct}. \tag{19}$$

This specification complements the cell-level analysis due to two important features. First, by pinpointing the theoretical victims of output conflict at the micro level, it represents an important falsification exercise. Second, by comparing the effects of PPI^{food} to PPI^{cash} between commercial farmers (or traders), we sidestep the main concern arising from our inability to control for individual fixed effects.[43] Our identifying assumption is that the impact of a food price shock on commercial food farmers is different to that of a cash crop price shock on commercial cash crop farmers only due to the fact that food prices deflate consumers' wages, conditional on the covariates listed above. Corollary 1 predicts that (18) and (19) are greater than zero.[44]

Results We display the results from our estimations of (17) in Table 7. The outcome variable is an indicator for theft in the first pair of columns, and for physical attack in the second pair. In columns (1) and (3), we estimate a variant of (17) that includes the CPI, country fixed effects and a country time trend instead of cell fixed effects and the country $\times$ year fixed effects. In columns (2) and (4), we estimate (17). We present the treatment effects from (18) and (19) in the second panel, together with each effect expressed as a percentage of the dependent variable means.

Focusing on commercial farmers, we see that impact of food crop prices relative to cash crop prices is positive and large across all four specifications. A standard deviation rise in food prices increases the probability that a commercial farmer experiences theft by 13.7% (p = 0.012), and physical violence by 12.9% (p = 0.101). The equivalent impacts in specifications that include the CPI are 14.7% (p = 0.005) and 18.4% (p = 0.02). The effect of the CPI itself is indistinguishable

[43]For example, if we excluded the cash crop comparison and focused only on $\sum_{k=0}^{n} \phi_{t-k}^{ff}$, we would be unable rule out the possibility that the effect of food price shocks on individuals' experience of theft and/or violence is moderated by factors correlated with being a commercial farmer. By focusing instead on the difference $\sum_{k=0}^{n} \phi_{t-k}^{ff} - \sum_{k=0}^{n} \phi_{t-k}^{cf}$, we hold these factors constant.

[44]We increase the statistical power of this test by making two straightforward adjustments to the data. First, we exploit time variation within survey rounds by replacing the annual average price data with six-monthly averages. This increases our temporal data points from 9 to 13. We adjust lags accordingly in regressions so that the sum of effects over two years are presented, as in the cell-level analysis. Second, we facilitate the inclusion of cell fixed effects by aggregating cells from 0.5 $\times$ 0.5 to 1 $\times$ 1 degrees. Without aggregating, we discard information on 9.855 observations from cells that feature in only one survey round; by aggregating, we discard only 3,929 single-cell observations.

from zero.

Turning to traders, we see that the impact is large and significant on theft, but not on violence. In our preferred specification, a one standard deviation rise in food prices increases the likelihood that traders report being victims of theft by 9.1% ($p = 0.008$). While the effect on physical attacks is comparable in magnitude (8%), it is much less precise ($p = 0.325$).

These results provide support for our theoretical prediction. 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. Traders are also more likely to experience theft, but not violence. We attribute these effects to the role of food prices as an income deflator for net-consumers, owing fundamentally to the relative price-inelasticity of demand for food crops relative to cash crops.[45]

5.4 Temporal and spatial structure of price effects

Our main specification models conflict in a given cell as a function of food prices in the contemporaneous and two previous years in that cell, and our main estimates report the sum of the contemporaneous and lagged effects. However, it is possible that own-cell price effects could have a longer lag structure (e.g. have effects on conflict that persist beyond two years), and/or that price shocks in one cell could affect conflict in nearby cells. Evidence of these spatial spillovers has been suggested by Harari and La Ferrara (2014) and Berman et al. (2017) in the context of shocks to local weather and mining activity respectively.

A primary challenge in our setting—and perhaps in related settings, although to our knowledge it has never been explored—is that our key independent variable is both temporally and spatially correlated. We show in a simulation in Appendix C.5 that while this makes it difficult to interpret the coefficient on any single spatial or temporal lag, with point estimates on correlated lags becoming increasingly noisy as autocorrelation is increased, the *sum* of either the temporal or spatial lags is remarkably stable and provides the overall effect of a single-year price shock over time and space (Figure A2). This simulation also suggests that in the presence of high autocorrelation in a regressor of interest, the increasingly common practice of including leads as a placebo test can be misleading, as large coefficients on each individual lead can be estimated even in the absence of a "true" effect.

Figures 5 and 6 show results from versions of our main specification that include temporal lags of up to 5 years, and spatial lags of up to annuli (concentric circles) with a radius of 500km. As in our simulation, coefficients on individual temporal or spatial lags are quite noisy, but their sum remains notably stable as increasing numbers of temporal/spatial lags are added. We find that our baseline results from the two-lag, no-spillover model are almost certainly conservative:

[45] We point readers a number of complementary exercises in the Appendix. In Appendix Tables A25 and A26 we show that an increase in the CPI increases self-reported poverty while an increase in the PPI reduces self-report poverty for farmers only. In Table A25 we show that the micro-level measures of output conflict are significantly correlated with the cell-level version of output conflict, and not with cell-level factor conflict. In Table A28, we show that the main results from Table 7 are similar when the price indices include trade weights. Finally, in Table A29, we show a placebo test in which the main results do not hold for non-commercial farmers.

allowing own-cell effects to persist up to five years roughly doubles the effect sizes for both factor and output conflict, and allowing a price shock in one cell to have effects up to 500km away also roughly doubles estimated overall effect sizes. We conclude that our baseline estimates are robust to inclusion of greater temporal and spatial lags, and likely conservative.

We then estimate versions of our main specification that include temporal lags of up to 5 years, and spatial lags of up to annuli (concentric circles) with a radius of 500km. As in our simulation, coefficients on individual temporal or spatial lags are quite noisy, but their sum remains notably stable as increasing numbers of temporal/spatial lags are added. As shown in Figures 5 and 6, we find that our baseline results from the two-lag, no-spillover model are almost certainly conservative: allowing own-cell effects to persist up to five years roughly doubles the effect sizes for both factor and output conflict, and allowing a price shock in one cell to have effects up to 500km away also roughly doubles estimated overall effect sizes. We conclude that our baseline estimates are robust and likely conservative.

5.5 Heterogeneity by subnational institutions

It is common in the conflict literature to examine the heterogeneity of effects by "institutions", which can take on a variety of meanings. In this context, we are particularly interested in institutions as the degree to which actors can rely on third parties to enforce contracts and protect property rights. In the presence of such institutions, actors can more credibly commit to upholding contracts instead of launching armed attacks.[46]

Rather than turning to the usual suite of country-level measures, we instead propose to harness our subnational data by exploiting a within-country measure of historical institutional capacity first recorded by Murdock (1957) and used by Michalopoulos and Papaioannou (2013). They show that the degree of political centralization within precolonial ethnic polities is strongly related to present-day economic development (as approximated by nighttime luminosity). To the extent that it persists over time, the sophistication of precolonial jurisdictional hierarchies is a plausible subnational measure of institutional quality as it relates to property rights.

To test this hypothesis, we interact our price indices with a dummy variable that indicates whether or not the level of precolonial political centralization went beyond the local village. The variable is measured at the level of an ethnic homeland (which is independent of modern day borders) and the value attributed to a cell is determined by the location of the cell's centroid. This feature allows us to control for country $\times$ year fixed effects in every specification.

We present the exercise and discuss the results in detail in Appendix Section C.6. Our main finding is that both the CPI and PPI have markedly diminished effects (in absolute terms) on factor conflict in cells associated a higher degree of political centralization. The PPI effect changes from -30.3% of the mean to $-30.3 + 23.7 = -6.6\%$, while the CPI effect is lower by -17.1%. With output conflict as the outcome, we see no significant effect of the PPI interaction. We also see that

[46] The argument that the emergence of the Leviathan state precipitated a dramatic decline in violence is documented in detail by Pinker (2012).

the CPI interaction effect is in fact positive, meaning that shocks are more likely to lead to output conflict in these cells relative to cells without a jurisdictional hierarchy beyond the local level. This suggests that output conflict is more likely to be triggered by CPI shocks where factor conflict is less of an option for would-be fighters. In any case, we can conclude that institutions—as they are measured here—play a role in mitigating the effect of prices shocks on large-scale factor conflict battles, but not on output conflict events.

5.6 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.[47] We first present results from a naïve specification in which the outcome variable alternates between the (country-level) incidence of UCDP conflict and the combined categories of all 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 remove the omitted variable bias and facilitate comparisons. For example, the PPI impact on UCDP conflict in the naive regression is -1.1% ($p = 0.795$); in the full country-level version it is -6.7% ($p = 0.155$); and in the full cell-level specification it is -17.2% ($p = 0.001$).

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 misrepresented account of the relationship between world food prices and conflict in Africa.

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

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 2004 and 2008. The consumer price impact on factor conflict incidence is +18.8% in terms of the sample mean, while the producer effect is −12.9%. 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 $+18.8 - 12.9(0.63) = +10.7\%$. For output conflict, we estimate an average consumer price impact of +31.5% across all cells, and a producer price impact of +14.2% in producer cells, giving a weighted average impact of around +40%. Our estimates show that rising crop prices have an unambiguously large, positive and significant effect on violence, whether in terms of large-scale factor conflict or smaller-scale output conflict. This stands in contrast to recent studies that estimate only negative partial effects through the producer channel (Berman and Couttenier, 2015; Fjelde, 2015; Bazzi and Blattman, 2014; Dube and Vargas, 2013; Brückner and Ciccone, 2010).

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 7. 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. Along with emerging research on conflict at the subnational level by, inter alia, Dube and Vargas (2013), Berman et al. (2017), and Harari and La Ferrara (2014), our results help to resolve ambiguity in the large body of existing country-level studies. Moreover, by identifying opposing effects of prices on the behavior of consumers and producers within countries, our study suggests that prior estimates in this literature are prone to attenuation.

Second, we advance knowledge on causal mechanisms. We exploit exogenous variation in world prices that generates opposing income shocks within countries. 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. Of course, this does not rule out the possibility that economic shocks can affect state counterinsurgency capacity in other contexts.

Third, we formalize distinctions between different forms of conflict. In cells where food crops are produced, higher prices reduce the incidence of "factor conflict" over the permanent control of territory, and *raise* the incidence of "output conflict" over the appropriation of surplus. 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 consider different varieties of conflict, as the failure to do so could lead to further attenuation. In addition, our results on output conflict add a new dimension to the "predation" motive, which was heretofore associated with the control of point-source commodity deposits rather than the small-scale but widespread appropriation identified in the present paper.

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. That our micro-level evidence is consistent with main analysis is reassuring, particularly in light of the recent emergence of geocoded conflict datasets and the promise of cell-level studies that avail of them.

Fifth, our results raise questions about the existing evidence on crop prices and conflict in the literature. While we too find that rising prices reduce conflict battles through the producer effect, we estimate that the consumer effect can be sufficiently large to reverse the overall impact, as in the case of the 2004-2008 price surge. Our key departure is that as crop prices rise, the locus of conflict risk will shift from rural to urban areas within countries. This aligns well with the outbreak of violence observed across Africa when prices approached historical peaks, from Arab Spring unrest in the north to incidences in Burkina Faso, Cameroon, and Mozambique, among others.

While our analysis provides strong evidence that economic conditions can cause violent conflict, it does not preclude an important role for other political or social grievances. Indeed, in our illustrations from Côte d'Ivoire, price shocks were accompanied by sectarian grievances in the lead up to the first civil war and by an election dispute in the second. In that example, at least, it seems that economic shocks exacerbated social or political divides. Nevertheless, we do reject claims that the link between income and conflict is unimportant or spurious.

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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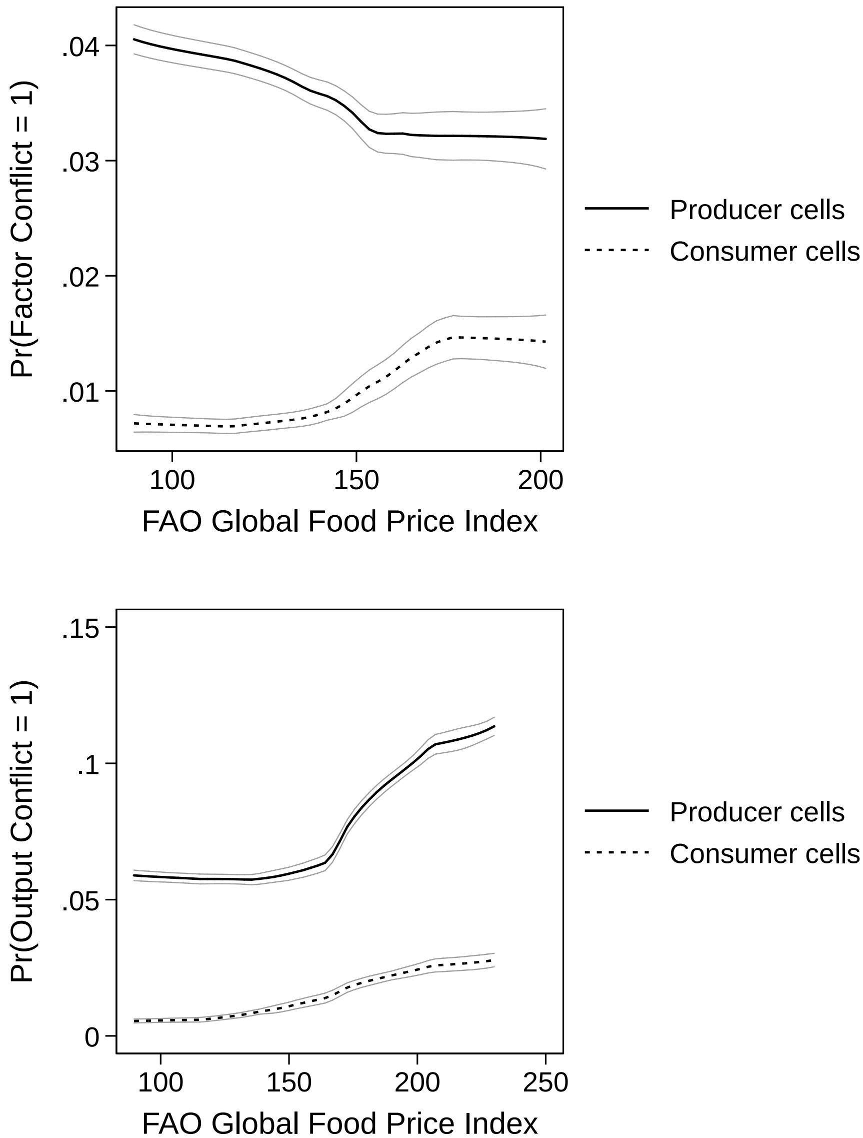
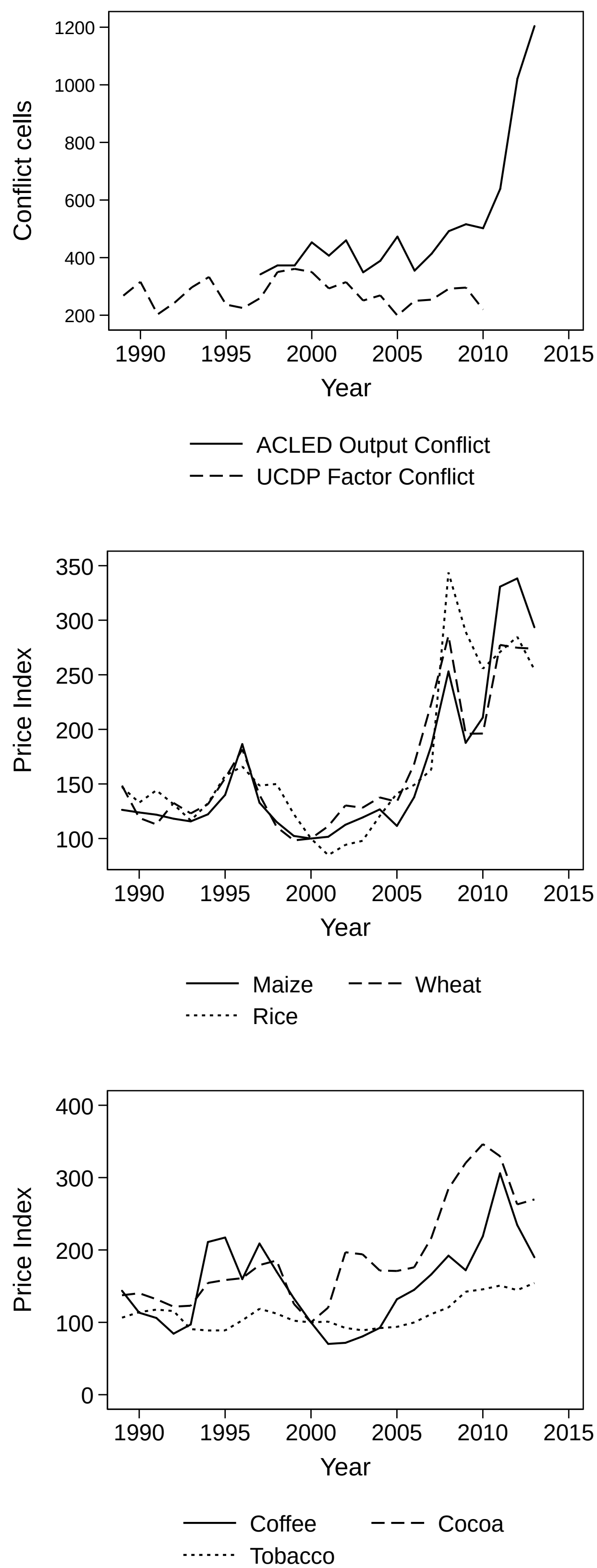
Figures

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: The geographic distribution of crops (year 2000) and total number of conflicts over the study period for the two conflict types.

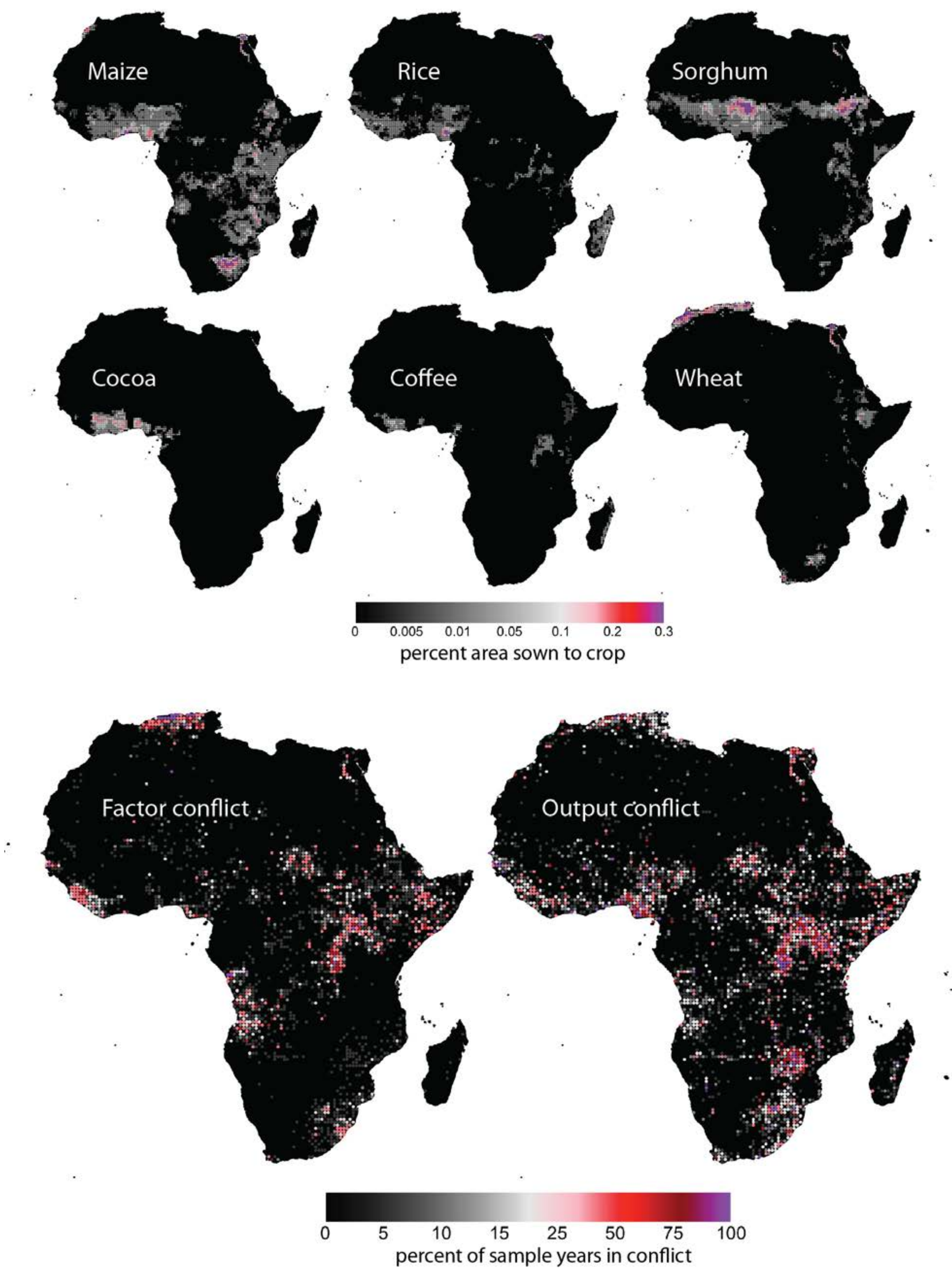
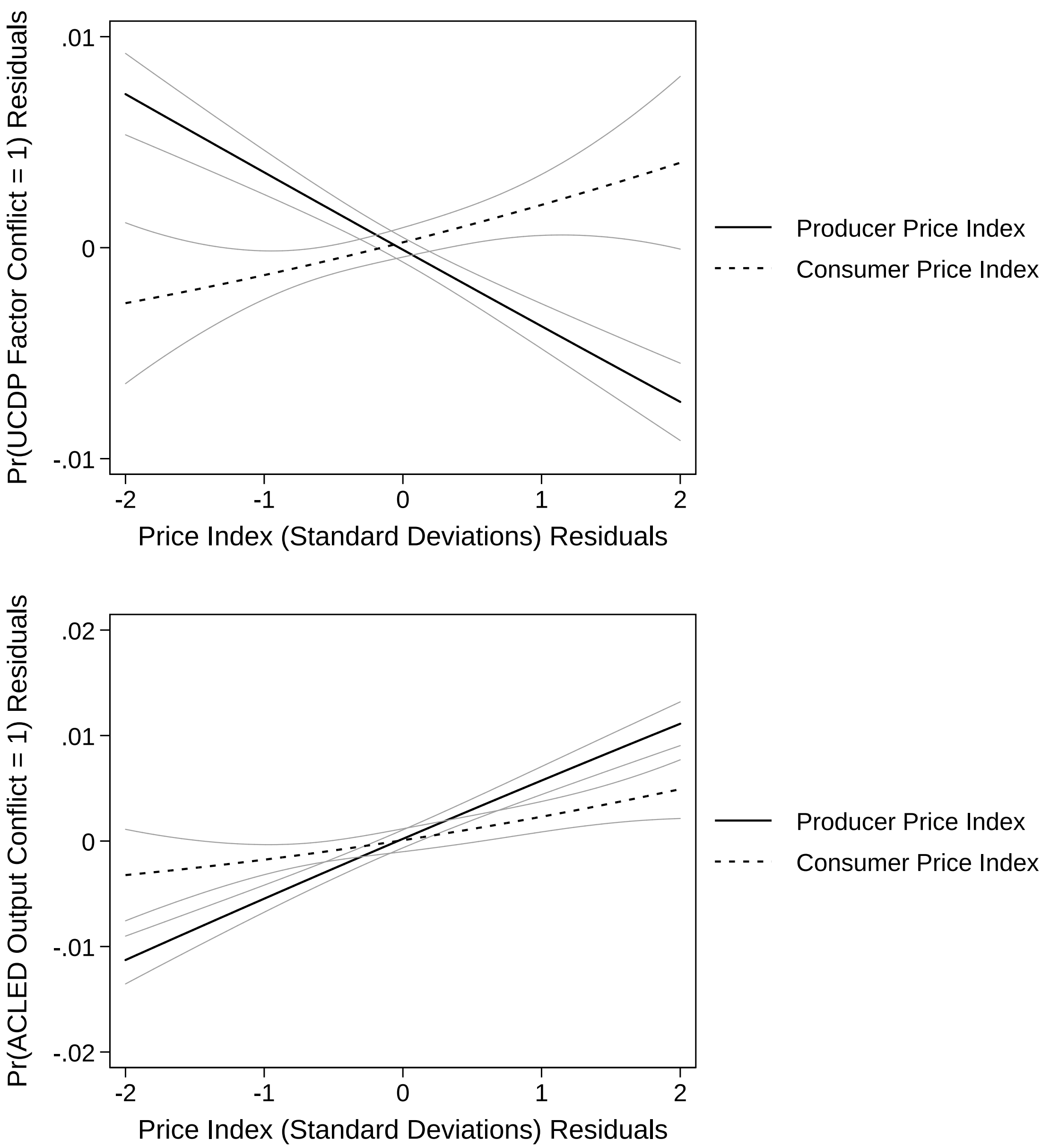


Figure 4: Impact of Prices on Factor Conflict and Output Conflict (Quadratic Fit)



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: **The temporal structure of food prices' effect on conflict**. *Top four plots*: cumulative effect of food price shock after n years. Each circle is from a separate regression, and shows the estimated cumulative effect of contemporaneous and lagged effects after n years, i.e. $\sum_{t-n}^{t} \beta_t$. Grey shaded area shows 95% confidence interval. Our baseline specification in the main text is the cumulative effect after 2 years, i.e. $\sum_{t-2}^{t} \beta_t$, and is shown as the solid black circle in each plot. Effects get larger in absolute value as more lags are added. *Bottom four plots*: individual effects for contemporaneous, lags, and leads, in a regression with 4 lags and 2 leads. Black dots show point estimate and 95% confidence for individual coefficients, blue dots show the cumulated effect of contemporaneous and lagged effects.

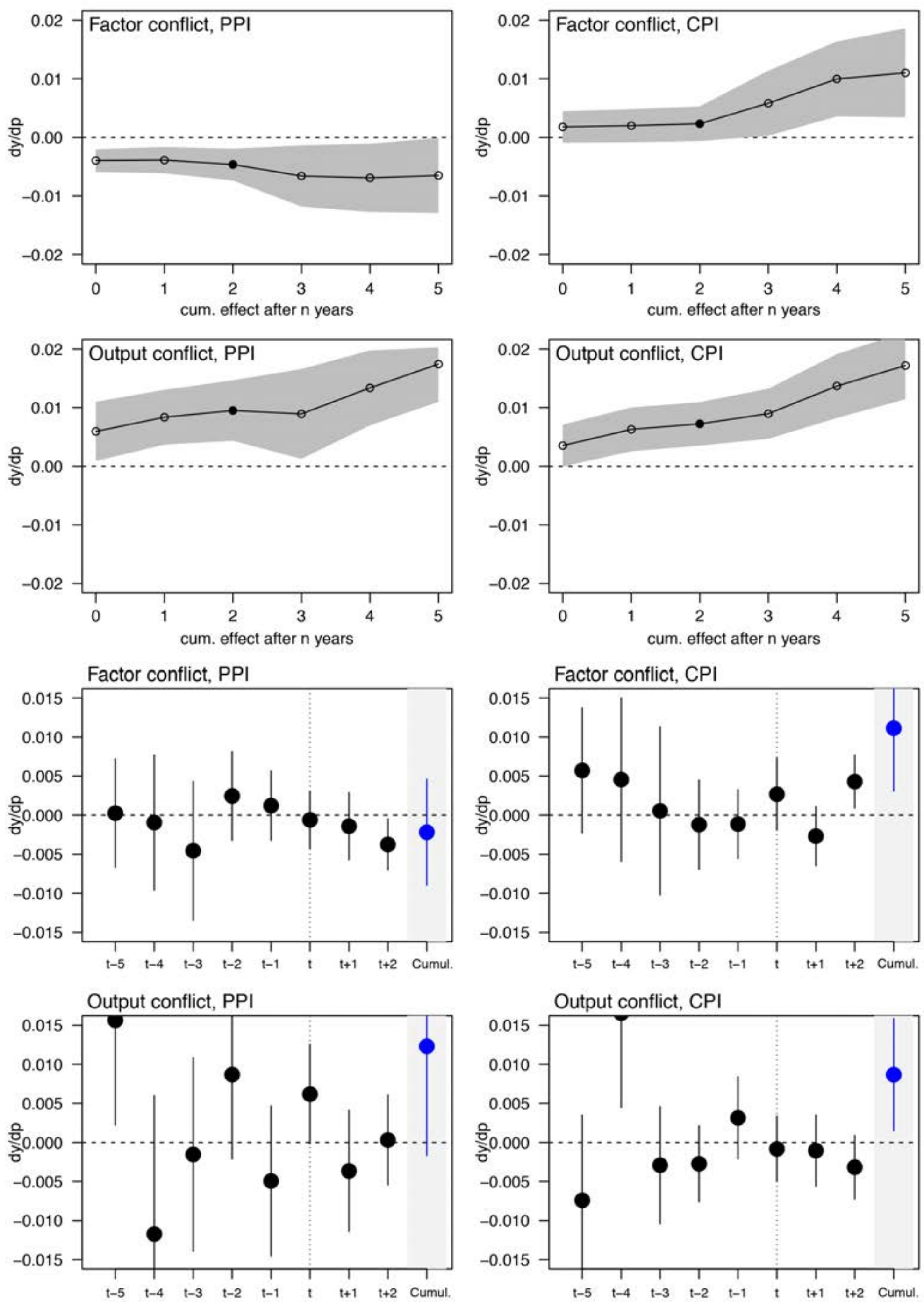


Figure 6: **The spatial structure of food prices' effect on conflict**. *Top plots*: the cumulative effect of a 1-SD producer shock in a given cell on conflict up to 500km away, for factor conflict (left) and output conflict (right). Each circle is from a separate regression, and shows the estimated cumulative effect of own-cell effect and spatial lag effect up to k kilometers. Grey shaded area shows 95% confidence interval. Our baseline specification in the main text assumes zero spatial lag, and is shown by the solid black dot. Effects get larger in absolute value as more spatial lags are added. *Bottom four plots*: individual effects for own-cell and spatial lags, from a regression that includes all spatial lags up to 500km. Individual coefficients are noisy, due to relatively high spatial autocorrelation in prices. Results are only computed for producer prices; consumer prices do not vary within country.

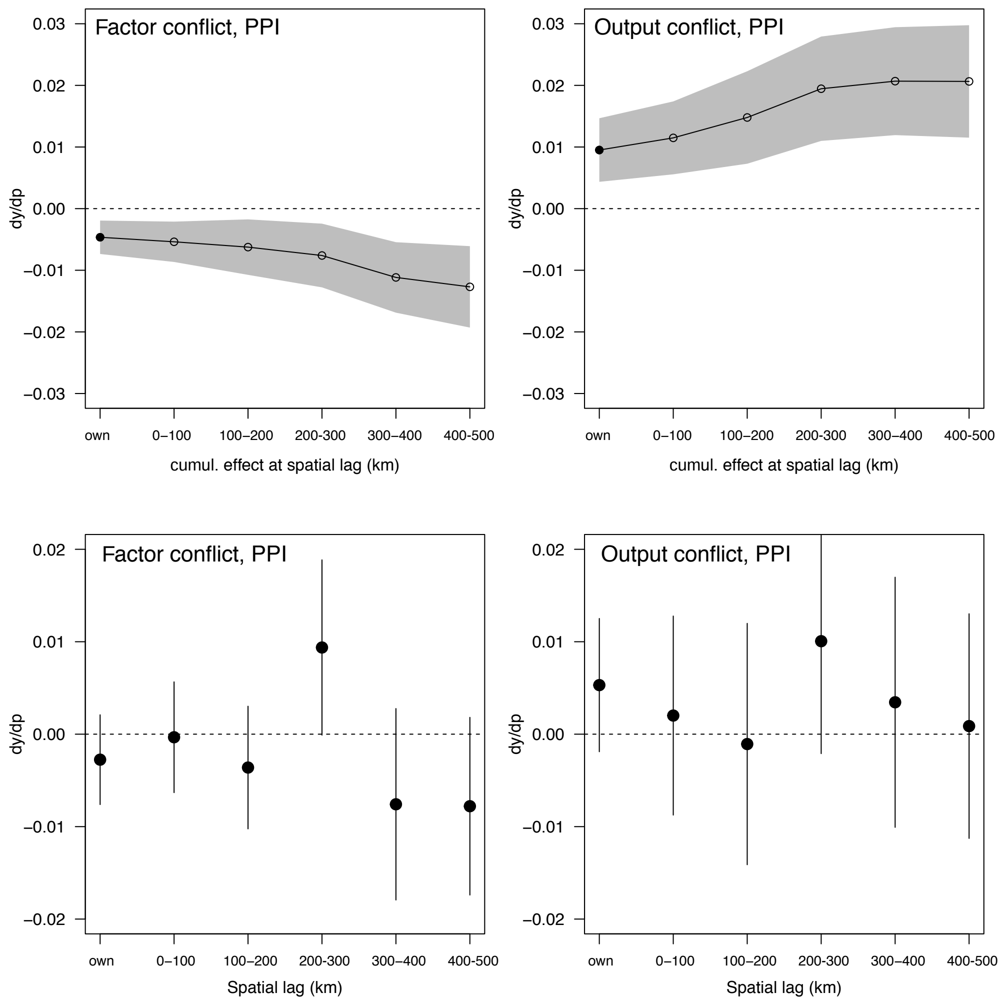
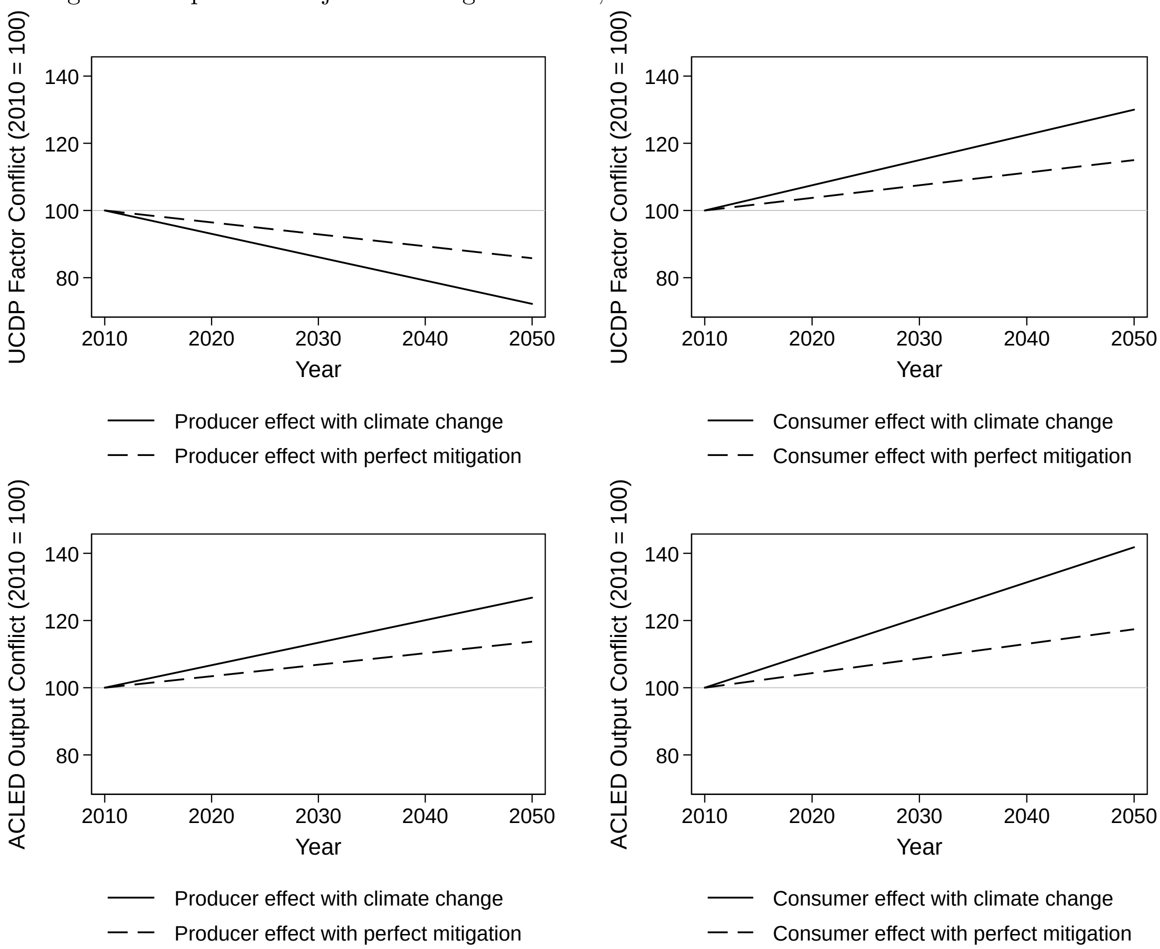


Figure 7: Impact of Projected Change to Maize, Rice and Wheat Prices from 2010 to 2050



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
Population	74092	236970	0	11620281	255725
Urban population	21269	187815	0	11045346	255725
Urban area %	0.009	0.039	0	0.87	255575
Distance to city with pop. $\geq$ 500k (in 100kms)	519	299	1	1441	255725
Luminosity 1992	0.24	0.427	0	1	255725
Luminosity 2010	0.396	0.489	0	1	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)
Producer Price Index	-0.0042	-0.0046	-0.0024	-0.0029	0.0443	0.0494
Conley SE	0.001	0.001	0.001	0.001	0.018	0.019
p-value	0.000	0.000	0.004	0.005	0.013	0.009
Two-way SE	0.002	0.001	0.001	0.001	0.022	0.023
p-value	0.007	0.001	0.020	0.006	0.043	0.029
Consumer Price Index		0.0023		0.0015		-0.0881
Conley SE		0.002		0.001		0.023
p-value		0.127		0.149		0.000
Two-way SE		0.001		0.001		0.026
p-value		0.116		0.161		0.001
PPI impact (%)	-15.4	-17.2	-16.3	-20.0	8.3	9.2
CPI impact (%)		8.6		10.2		-16.5
Wald test: PPI = CPI						
Conley p-value		0.000		0.000		0.000
Two-way p-value		0.000		0.002		0.001
Country × year FE	Yes	No	Yes	No	Yes	No
Country × time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225016	204820	222132	202297	5108	4631

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 respectively in terms of average temporal standard deviations. Reported effects are the sum of price coefficients at t, t-1 and t-2: $\sum_{t-2}^{t} \beta_t$. Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way 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 4: UCDP Factor Conflict, Prices and Luminosity

	Factor Conflict Incidence: 1(Conflict > 0)					
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	-0.0079	-0.0510	-0.0102	-0.0502	-0.0083	-0.0484
Conley SE	0.002	0.018	0.002	0.018	0.002	0.018
p-value	0.000	0.005	0.000	0.005	0.000	0.008
Two-way SE	0.002	0.032	0.003	0.032	0.003	0.032
p-value	0.000	0.111	0.001	0.116	0.008	0.131
Producer Price Index × Luminosity	0.0049	0.0041	0.0072	0.0051	0.0050	0.0032
Conley SE	0.002	0.002	0.002	0.002	0.002	0.002
p-value	0.002	0.014	0.000	0.011	0.017	0.128
Two-way SE	0.002	0.002	0.003	0.003	0.003	0.003
p-value	0.007	0.019	0.010	0.073	0.098	0.272
Producer Price Index × Dist. to lights		0.0820		0.0774		0.0774
Two-way SE		0.060		0.060		0.060
p-value		0.171		0.198		0.196
Producer Price Index × Dist. to port		0.0001		0.0001		0.0000
Two-way SE		0.000		0.000		0.000
p-value		0.869		0.835		0.929
Producer Price Index × Dist. to border		0.0016		0.0018		0.0018
Two-way SE		0.001		0.001		0.001
p-value		0.175		0.141		0.120
Producer Price Index × Dist. to capital		-0.0005		-0.0005		-0.0005
Two-way SE		0.001		0.001		0.001
p-value		0.462		0.487		0.458
Consumer Price Index × Luminosity	-0.0040	-0.0006	-0.0060	-0.0031	-0.0060	-0.0030
Conley SE	0.002	0.001	0.002	0.001	0.002	0.001
p-value	0.022	0.683	0.000	0.030	0.000	0.038
Two-way SE	0.003	0.002	0.003	0.002	0.003	0.002
p-value	0.196	0.788	0.027	0.123	0.032	0.224
Consumer Price Index × Dist. to lights		-0.1990		-0.2011		-0.2020
Two-way SE		0.126		0.127		0.128
p-value		0.115		0.115		0.115
Consumer Price Index × Dist. to port		0.0023		0.0022		0.0022
Two-way SE		0.001		0.001		0.001
p-value		0.004		0.005		0.005
Consumer Price Index × Dist. to border		-0.0017		-0.0017		-0.0017
Two-way SE		0.001		0.001		0.001
p-value		0.056		0.052		0.055
Consumer Price Index × Dist. to capital		0.0000		-0.0001		-0.0001
Two-way SE		0.001		0.001		0.001
p-value		0.988		0.892		0.882
PPI impact (%)	-29.1	-188.7	-37.9	-185.6	-30.5	-179.1
PPI impact (%) × Luminosity	18.1	15.1	26.6	18.9	18.5	11.9
CPI impact (%) × Luminosity	-14.7	-2.2	-22.3	-11.5	-22.2	-11.1
Luminosity year	1992	1992	2000	2000	2010	2010
Trade weight	No	No	No	No	No	No
Country × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Extra Controls	No	Yes	No	Yes	No	Yes
Observations	203962	199584	203962	199584	203962	199584

Note: The dependent variables is UCDP Factor Conflict incidence. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured respectively in terms of average temporal standard deviations. Reported effects are the sum of price coefficients at t, t-1 and t-2: $\sum_{t-2}^{t} \beta_t$. Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way 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. *Luminosity* = 1 if any light is visible at night from satellite images in a given cell. All specifications include a time-varying cell-level control for population.

Table 5: ACLED Output Conflict Incidence, Combined 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	0.0076	0.0095	0.0068	0.0080	0.0092	0.0069
Conley SE	0.002	0.002	0.002	0.002	0.003	0.005
p-value	0.000	0.000	0.000	0.000	0.002	0.207
Two-way SE	0.003	0.003	0.002	0.002	0.005	0.006
p-value	0.007	0.000	0.004	0.000	0.044	0.243
Consumer Price Index		0.0072		0.0033		-0.1271
Conley SE		0.002		0.001		0.017
p-value		0.000		0.010		0.000
Two-way SE		0.002		0.001		0.019
p-value		0.000		0.015		0.000
PPI impact (%)	15.1	18.9	47.2	55.7	1.7	1.3
CPI impact (%)		14.4		22.9		-23.8
Country × year FE	Yes	No	Yes	No	Yes	No
Country × time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	173876	158270	169933	154795	7410	6774

Note: The dependent variables are dummies for ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured respectively in terms of average temporal standard deviations. Reported effects are the sum of coefficients on price variables at t, t-1 and t-2: $\sum_{t-2}^{t} \beta_t$. Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way 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 and Disaggregated Producer Prices

	Incidence 1(Conflict > 0)	Onset 1(Conflict Begins)	Offset 1(Conflict Ends)
	(1)	(2)	(3)
Producer Price Index: Food crops	0.0083	0.0072	0.0076
Conley SE	0.002	0.002	0.003
p-value	0.000	0.000	0.006
Two-way SE	0.003	0.002	0.004
p-value	0.001	0.000	0.061
Producer Price Index: Cash crops	-0.0026	-0.0014	0.0118
Conley SE	0.002	0.002	0.005
p-value	0.100	0.359	0.010
Two-way SE	0.002	0.002	0.007
p-value	0.225	0.461	0.082
PPI Impact: Food crops	16.6	25.5	1.7
PPI Impact: Cash crops	-5.2	-5.0	2.6
Wald test: PPI Food = PPI Cash			
Conley p-value	0.000	0.000	0.434
Two-way p-value	0.000	0.000	0.522
Country × year FE	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes
Observations	173876	169933	7410

Note: The dependent variables are dummies for ACLED Output Conflict incidence, onset and offset dummies. The price indices are measured respectively in terms of sample average temporal 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). Reported effects are the sum of coefficients on price variables at t, t-1 and t-2: $\sum_{t-2}^{t} \beta_t$. Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI impact* indicates the effect of a one standard deviation rise in 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	0.0027	0.0017	-0.0000	-0.0003
SE	0.002	0.001	0.001	0.001
p-value	0.165	0.059	0.970	0.813
Producer Price Index: Food crops × farmer	0.0014	0.0008	0.0011	0.0000
SE	0.002	0.002	0.001	0.001
p-value	0.459	0.748	0.368	0.995
Producer Price Index: Food crops × trader	0.0041	0.0046	0.0020	0.0022
SE	0.002	0.002	0.001	0.001
p-value	0.086	0.046	0.172	0.116
Producer Price Index: Cash crops	-0.0023	-0.0089	0.0053	-0.0212
SE	0.013	0.015	0.010	0.007
p-value	0.855	0.547	0.587	0.004
Producer Price Index: Cash crops × farmer	-0.0447	-0.0422	-0.0229	-0.0169
SE	0.015	0.015	0.010	0.009
p-value	0.004	0.006	0.017	0.078
Producer Price Index: Cash crops × trader	-0.0319	-0.0237	-0.0126	-0.0082
SE	0.017	0.009	0.018	0.010
p-value	0.058	0.014	0.477	0.420
Consumer Price Index	0.0006		-0.0005	
SE	0.002		0.002	
p-value	0.742		0.744	
Treatment effects				
(PPI Food − PPI Cash) × farmer	0.0461	0.0430	0.0240	0.0169
SE	0.016	0.017	0.010	0.010
p-value	0.005	0.012	0.020	0.101
Impact on farmers (%)	14.7	13.7	18.4	12.9
(PPI Food − PPI Cash) × trader	0.0360	0.0284	0.0146	0.0105
SE	0.017	0.010	0.018	0.011
p-value	0.036	0.008	0.417	0.325
Impact on traders (%)	11.5	9.1	11.2	8.0
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
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 terms of average temporal 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). Reported effects are the sum of coefficients on price variables at t through t-4: $\sum_{t-4}^{t} \beta_t$, 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 and spatial correlation within 1 degree cells. *PPI impact* indicates the effect of a one standard deviation rise in 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. Reported effects are the sum of coefficients on price variables at t, t-1 and t-2: $\sum_{t-2}^{t} \beta_t$. 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:

$$\Delta P_{jt} = \alpha + \beta P_{jt-1} + \zeta_1 \Delta P_{jt-1} + \zeta_2 \Delta P_{jt-2} + \ldots + \zeta_k \Delta P_{jt-k} + \epsilon_t \tag{20}$$

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 (20) 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 A5 and Figure A6 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.[48]

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

[48] 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 $\frac{N}{2} + \omega$, and group 2 controls $\frac{N}{2} - \omega$. 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

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

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

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

It follows that the transfer must satisfy

$$\mathbf{P} \cdot \frac{\mathbf{N}}{2} > \pi(1 - v)[\mathbf{P} \cdot \mathbf{N}]. \tag{21}$$

The is the condition for peace in the presence of bargaining. Two observations are noteworthy. First, ω 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 (21) does not hold, bargaining cannot affect the prospect of violence caused by the first-mover advantage.

Rearrange condition (21), conflict occurs if

$$\pi > \pi^w \equiv \frac{1}{2(1-v)}. \tag{22}$$

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 again applying Chassang and Padro i Miquel (2009) to our setting. Consider the continuation value of peace as the highest solution to the following equation:

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

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

$$\tilde{V}^P = \frac{\bar{Y}}{2(1-\delta)} - \frac{vF(\tilde{\mathbf{P}})\mathbb{E}(\mathbf{P}\cdot\frac{\mathbf{N}}{2} \mid \mathbf{P} < \tilde{\mathbf{P}})}{1-\delta\left(1-F(\tilde{\mathbf{P}})\right)} \tag{23}$$

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 (2) with equality. We substitute in (3) and (23) and rearrange to find

$$\tilde{\mathbf{P}} = \frac{\delta}{1-2\pi(1-v)}\left[(2\pi-1)\frac{\bar{\mathbf{P}}}{1-\delta} + \frac{vF(\tilde{\mathbf{P}})\mathbb{E}(\mathbf{P} \mid \mathbf{P} < \tilde{\mathbf{P}})}{1-\delta\left(1-F(\tilde{\mathbf{P}})\right)}\right]. \tag{24}$$

Existence of $\tilde{\mathbf{P}}$ is guaranteed because the right hand side is always strictly positive, bounded and continuous.[49] 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 (24). As above, for any first-mover advantage that yields $\pi > \pi^W$, there is no equilibrium that

[49]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.

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.

Testing for stationarity in the PPI and CPI We run Haris-Tzavalis unit root tests for both the PPI and CPI, as it is particularly suitable for cases with large N panel data. Including panel means and time trends, we report ρ statistics of 0.73 (p-value = 0.00) and 0.65 (p-value = 0.00) respectively, and reject the hypothesis that the panels contain unit roots.

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 ("type 2" event in ACLED). This has the advantage of capturing events that are consistent our theoretical definition of factor conflict. However, it comes at the expense of coverage: with a sample mean of only 0.04%, it omits many valid factor conflict battles. 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).[50]

[50]This would lead to non-classical measurement error that would bias our PPI estimate toward zero.

C Additional results

C.1 Robustness of factor conflict results

Additional covariates In Table A2, we cumulatively add (i) year fixed effects; (ii) cell-level weather covariates and oil prices × cell- and country-level production indicators; and (iii) mineral prices × cell-level mine indicators from Berman et al. (2017). 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). 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 control for two mechanisms through which oil prices can affect cell-level factor conflict. First, higher prices in oil producing cells could increase violence by either funding 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). We obtain geocoded data on the location of oil fields in Africa from the PRIO Petroleum Dataset.[51] We combine this with IMF data on world oil prices to produce two oil variables: an oil price × cell-level dummy for the presence of an oil field and an oil price × country-level dummy for oil producers. Finally we take the cell-level mine and mineral price variables directly from Berman et al. (2017).

As we note in the main text, all PPI effects remain significant, and five of the eight CPI effects are under or at the 10% level of significance with Conley SEs, which are smaller than two-way clustered SEs. We also note that the CPI effect is significant when interacted with luminosity (see Table A3 and related discussion) and when interacted with subnational institutions (see Table A30 and related discussion).

Additional robustness We additionally show that the results are robust to recoding the outcome variable as "two-sided" conflict only (Table A3), which guarantees the presence of a non-state armed group in the data; to varying the Conley standard error kernal cutoff from 100km to 1000km in increments of 100km (Table A4); to aggregating the cell area to 1 degree cells (i.e., by a factor of four; Table A5) to assuage fears that the results are overstated due to the resolution of the

[51]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

data (we refer the reader to Section C.5 for an explicit treat of spatial effects); to adding to that specification controls for the PPI in neighboring cells (Table A6); to including a cell-year estimate of population as a control variable (Table A7), which we create by extrapolating over five-yearly cell-level estimates provided by SEDAC (described in the main text); to estimating a conditional fixed-effects logit model (Table A8); to weighting the CPI and PPI components by the extent to which crops are traded by a given country (Table A9; these 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. We also include results with the trade weight calculated at baseline; [52] to weighting the PPI by crop yields per hectare (Table A10);[53] and including contemporaneous price indices only (Table A11).

C.2 Robustness of output conflict results

In Table A12, we again cumulatively add (i) year fixed effects; (ii) cell-level weather covariates and oil prices × cell- and country-level production indicators; and (iii) mineral prices × cell-level mine indicators from Berman et al. (2017). The results are discussed in the main draft. They suggest that the CPI effect is largely a common shock across countries. However, when we introduce more spatial variation to the CPI by interacting it with measures of urbanization (see Table A23 and related discussion below), we see it is significant in the presence of country × year fixed effects.

We also show that the results are qualitatively robust to recoding the outcome variable as "riots" only (Table A14); varying the Conley standard error kernal cutoff from 100km to 1000km in increments of 100km (Table A15); aggregating the cell area to 1 degree cells (i.e., by a factor of four; Table A16); adding to that specification controls for the PPI in neighboring cells (Table A17); including a cell-year estimate of population as a control variable (Table A18); estimating a conditional fixed-effects logit model (Table A19); weighting the CPI and PPI components by the extent to which crops are traded by a given country (Table A20); weighting the PPI by crop yields per hectare (Table A21); and including contemporaneous price indices only (Table A22).

Is output conflict just urban protests? 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

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

[53] Crop yield in a given cell is from (Ramankutty et al. 2008). The index then contains:

$$PPI_{ict} = \sum_{j=1}^{n} (P_{jt} \times N_{jic} \times Yield_{jic}),$$

where the price and the yield are measured in the same units. This reduces the size of the PPI effect in both sets of regressions (Tables A10 and A21); for output conflict, almost all estimates are still significant; for factor conflict, only the offset estimate is significant (with country × year FE). These results are consistent with the estimated yield components introducing additional measurement error to the PPI, which we view as plausible given that these yield estimates are very highly interpolated/estimated for much of Africa (few countries report subnational yield estimates, so the data product we use here is heroic in that respect). While we are reassured that the results remain qualitative unchanged at least, we prefer our original measure, as it provides adequate spatial variation with less measurement error.

means of acquiring output as their real incomes fall. However, work by Bellemare (2015) and others show that higher food prices can cause 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. 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 independent CPI term strongly suggests that the overall effect is not explained fully by protest riots.

Results are given in Table A23. In column (1), both the interaction term *CPI* $\times$ *urban area* and the CPI term are significantly different from zero. In the 90th percentile of urbanization, a standard deviation rise in the CPI in increases output conflict by 20%; when urban area is equal to zero, the same change still increases output conflict by 11.1%. 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. (This also provides important evidence of the CPI effect on output conflict in the presence of country $\times$ year effects.) In columns (3) and (4) the interaction term CPI $\times$ 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 fully by urban protests designed to create unrest and agitate for policy reforms. Output conflict occurs in non-urban as well as urban areas. 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 over time periods

In Table A24 we compare our results on output conflict and on factor conflict over the same period in order to investigate whether the contrasting impact of the PPI on both outcomes can be fully explained by the different sample periods or data collection organizations. We discuss the principal results in the main text, concluding that our results are neither an artifact of differences between the study periods nor the data sources.

Here, we discuss in more detail the difference between the PPI impacts on ACLED Territorial Change in the 1997-2010 sample and the 1997-2013 sample, which go from -15% to -2.6%. One explanation could be that world food prices reached a historical peak in 2011 (see Figure A4), which precipitated not just a wave of output conflict events, as we discuss in the paper, but also an intense wave of factor conflict events in urban areas, such as the "Arab Spring" related violence in North Africa and the Second Ivorian Civil war (note the 33.2% CPI effect). In the presence of even small spillovers, this could have the effect of biasing the PPI effect on factor conflict toward zero. This is because CPI-triggered conflict events that spillover from urban to rural areas will show up as a positive association between the PPI and factor conflict. The reverse is not necessarily true, as conflict originating in rural areas generally spillover into other rural areas.

While we unfortunately do not have cell-level measures of the CPI to get an accurate sense of spillovers from CPI shocks, we can still interrogate this theory by examining the effect of the PPI on ACLED Territorial Change in areas further away from cities. We do this by (i) aggregating to larger 1 degree (110km $\times$ 110km) cells; and (ii) interacting the PPI with a dummy variable indicating that the (larger) cell has no urban center. We find that the PPI effect is -0.002, or -15.4% of the (larger, 1 degree) mean, with a p-value of 0.06. Interestingly, when we restrict the years as in column (4) to 1997-2010, we find a similar result: -0.003, or -23.7% of the mean, with a p-value of 0.08.[54]

In the end, it appears that spillovers from CPI shocks may bias PPI effects on factor conflict towards zero during the historically high price shock of 2011/12. Much of this spillover effect can be sidestepped when we estimate the PPI effect in rural areas at least 110km (roughly) from urban centers. Finally, even when we do not account for this (as in Table A26), it is still the case that the PPI and CPI effects are significantly different to each other in all factor conflict regressions (in all periods) and in no output conflict regressions.

C.4 Afrobarometer results

Food prices and self-reported poverty In Table A25, we examine the effect of the producer and consumer price indices on three different self-reported poverty measures. In columns (1)-(3), 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 (4)-(6) the outcome variable indicates that the household has frequently gone without income over the preceding year, and in columns (7)-(9) 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 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 0.9%. The equivalent

[54] Results are available on request.

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 ($\sim 0.5\%$) 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.[55]

Validation tests In Table A27, 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.

C.5 Temporal and spatial lags

Here we explore in more detail the temporal and spatial structure of the effect of food price shocks on conflict. Our main specification models conflict as a function of food prices in the contemporaneous and two previous years, and our main estimates report the sum of the contemporaneous and lagged effects. Reporting the sum of contemporaneous and lagged effects has at least two advantages. First, it is a straightforward way to account for potential displacement and/or for persistence. For instance, if displacement effects of food prices shocks are are large, contemporaneous and lagged effects will have opposite sign and their sum will be close to zero; if instead the price shocks have persistent effects, then the sum of contemporaneous and lagged effects will generally be larger than just the contemporaneous effects (Burke et al., 2015). Second, as we explore below, when an

[55]We note that the CPI effect is substantially larger when the price indices are adjusted to account for trade weights (Table A26).

independent variable of interest is highly correlated over time or space, individual coefficients on contemporaneous or lagged effects can be very noisy, but the sum of the coefficients is stable and quite close to the "true" cumulated effect size. The choice of two lags is somewhat arbitrary, and below we explore robustness to the inclusion of more or fewer lags.

Our main estimates also do not explicitly account for spatial spillovers. However, as recent work in the conflict literature has emphasized (Harari and La Ferrara, 2014; Berman et al., 2017), both conflicts and their causes could be correlated over space, and failure to account for this spatial dependence could lead to biased estimates – or at the very least an unclear picture of how the effects of a given conflict-inducing shock diffuse through space. Nevertheless, as noted by Berman et al. (2017) and other authors, there are substantial difficulties in identifying spillovers. Including spatial lags of the outcome variable introduces clear concerns about simultaneity bias, and this problem cannot necessarily be solved by instrumenting with spatial lags of the independent variable if (as in our case) this variable is itself highly spatially correlated. Echoing one of the approaches taken in Harari and La Ferrara (2014), our approach instead is to focus on spatial lags of the independent variable, as these appear to induce fewer identification concerns.

We proceed as follows. First we show the patterns of spatial and temporal autocorrelation in our independent variable, and then explore in simulation (under a known DGP) what these magnitudes of autocorrelation imply about how temporal and spatial lags should be estimated. We show below why, for nearly all our results, our choices in the main text likely yield a conservative estimate of the overall impact of food price shocks. Furthermore, we show that an increasingly common placebo test in applied panel econometrics – the regression of current values of a dependent dependent variable on future values of an independent variable (i.e. "leads") – can be misleading in a setting of high autocorrelation in the independent variable.

Observed spatial and temporal autocorrelations Figure A1 shows the observed temporal and spatial autocorrelation in our two price variables. Average temporal correlations are calculated across lags up to $t-4$ for both CPI and PPI price variables and are quite high, particularly for PPI. Spatial correlations are calculated by first constructing 100km annuli (concentric circles) around every cell in our study out to 500km, and calculating the average prices in each annuli-year around each cell. The middle panel of Figure A1 then reports the average correlation between the price in a given cell-year and the prices in each annuli out to 500km in that year. As expected, consumer prices (which don't vary within country but can vary across country borders) are more highly spatially correlated than producer prices (which do vary within country). The right panel visualizes the size of these spatial annuli for a randomly chosen cell; in this example for a cell in Uganda, the 500km annuli would include price information from Uganda, DR Congo, Rwanda, Burundi, Kenya, and South Sudan. The diameter of the outer annulus is roughly the width of Kenya.

Understanding lagged effects in the presence of autocorrelation To understand the effect of autocorrelation in the independent variable on estimated coefficients in a temporal/spatial lag model, we simulate a data generating process where an outcome y depends linearly on contemporaneous x and four lags of x:

$$y_t = \sum_{t-4}^{t=0} \beta_t x_t + \eta_t \tag{25}$$

with $\beta_t = 5$, $\beta_{t-1} = 4$, $\beta_{t-2} = 3$, $\beta_{t-3} = 2$, $\beta_{t-4} = 1$. η is a mean zero white noise term. In this setup, t can index either temporal lags (e.g. years) or spatial lags (e.g. annuli: concentric circles at increasing distance from an origin).

We then construct the x variables to have either high (temporal or spatial) autocorrelation (correlations: $\rho_{x_t,x_{t-1}} = 0.98$, $\rho_{x_t,x_{t-4}} = 0.9$), or somewhat lower autocorrelation ($\rho_{x_t,x_{t-1}} = 0.9$, $\rho_{x_t,x_{t-4}} = 0.7$), to roughly match the range of temporal and spatial autocorrelations we see in our data (Figure A1). We then take a draw of η and generate y_t via Equation 25. To mimic increasingly-common practice in applied work, we then estimate Equation 25 also including two "leads" (i.e. x_{t+1} and x_{t+2}) as regressors, which are interpreted as placebo tests. By construction in (25), these leads have no effect on the outcome in time t. This process is repeated 100 times separately for the high autocorrelation values and the lower autocorrelation values, and the estimated β_t are saved in each run.

Results of this simulation are shown in Figure A2. We extract three insights. First, as expected in the presence of autocorrelation in the x variables, the estimated coefficient on any particular lag is unbiased but quite noisy. Individual coefficient estimates in some runs have the wrong sign, and in others are two times too large or larger, particularly in the high autocorrelation simulation. Second, while individual coefficients are noisy, the *cumulative* effect ($\sum_{t-4}^{t=0} \hat{\beta}_t$ is much more precisely estimated (as shown on the right-hand-side of both figure panels), with the noise in each individual coefficient canceling out as coefficients are summed. Third, and somewhat surprisingly, individual coefficients on the (placebo) lead variables are often large and in some cases larger than the contemporaneous effect, even though by construction these lead variables have no "true" effect on the outcome. This suggests that, in the presence of temporal autocorrelation in the independent variable, the now-standard practice of including leads in a panel regression could lead to misplaced concern that a specification "fails" a placebo test. Our results suggest that with reasonably high autocorrelation, these false positives could be somewhat common.

Empirical results on spatial and temporal spillovers Our main specification models conflict in cell i as a function of food prices in the contemporaneous and two previous years in cell i. Guided by the above simulation, we now explore how results differ when we add or subtract temporal lags, and when we add spatial lags. For temporal lags, we estimate 6 models: a model with no lags, a model with one lag, a model with two lags (our baseline model) and so-on up to 5 lags. For consistency with the literature, we also include two leads as "placebo" tests. The empirical specification that includes all five lags is thus:

$$factor\ conflict_{ict} = \alpha_i + \sum_{k=-5}^{2} \beta^{p}_{t+k} PPI_{ict+k} + \sum_{k=-5}^{2} \beta^{m}_{t+k} CPI_{ct+k} + \gamma_c \times trend_t + \epsilon_{ict} \tag{26}$$

where i denotes cell, c denotes country, and $t - k$ denotes year. Results are shown for factor and output conflict in Figure 5. The top four plots show the cumulative effects of prices on conflict for models with increasing numbers of lags, for both types of conflict and both consumer and producer prices. The bottom four plots show estimated individual coefficients in the 5-lag, 2-lead model (Equation 26). Consistent with the simulation, individual coefficients are noisy but cumulative effects are remarkably stable and more precisely estimated. Moreover, these results indicate that cumulative effects from our baseline 2-lag model reported in the main text are somewhat conservative relative to models with higher numbers of lags. Estimates for the "placebo" leads are also noisy, but in a few cases are significantly different than zero (e.g. the $t + 2$ lead in the CPI/output conflict regression). However, given the simulation results above, we do not conclude that our results "fail" the placebo test; rather, it seems that this placebo test is likely uninformative in the context of autocorrelated regressors.

To study spatial spillovers, we amend our main specification to include cumulative and lagged prices shocks in annuli up to 500km (as depicted in the right panel in Figure A1). We focus on PPI impacts as the CPI does not vary within country. For the model with annuli out to 500km, the specification is thus:

$$factor\ conflict_{ict} = \alpha_i + \sum_{k=-2}^{0} \beta_{t+k} PPI_{ict+k} + \sum_{a=100}^{500} \sum_{k=-2}^{0} \beta^{a}_{t+k} PPI^{a}_{ict+k} + \gamma_c \times trend_t + \epsilon_{ict} \tag{27}$$

where a designates annuli in 100km increments. This yields a regression with 18 price variables.

Similar to the temporal results, the individual coefficients on the spatial lags are noisy, but their sum is more precisely estimated and grows as increasing spatial lags are added. As shown in the top panels of Figure 6, the overall effect of a PPI shock on conflict increases as more spatial lags are added, and including impacts up to 500km away roughly doubles the overall effect size relative to our baseline model with no spatial lags. This is true for both factor and output conflict. As in the simulation, individual coefficient estimates are substantially noisier (bottom panels).

C.6 Heterogeneity by subnational institutions

We harness the richness of our subnational data by exploiting a within-country measure of historical institutional capacity first used by Michalopoulos & Papaioannou (2013). In this literature, 'institutions", or more specifically the extent to which actors can rely on third parties to credibly enforce contracts and protect property rights, are thought to be a first-order determinant of peace. Michalopoulos & Papaioannou document that the degree of political centralization within precolonial ethnic homelands is strongly related to present-day economic development (as approximated by nighttime luminosty), controlling for country-level factors. To the extent that it persists over time, the sophistication of precolonial jurisdictional hierarchies is a plausibly suitable measure of institutional quality in relation to property rights.

To test this hypothesis, we interact our price indices with a dummy variable that indicates whether or not the level of precolonial political centralization went beyond the local village. The variable is measured at the level of an ethnic homeland (which is independent of modern day borders) and the value attributed to a cell is determined by the location of the cell's centroid.

We present the effect of this interaction term on factor conflict in Table A30. In the first column, as in our similar exercise on heterogeneity by luminosity in Table 3, we include country × year fixed effects as well as a control for population (a potential omitted variable). In the second column, we introduce the battery of controls included in the full specifications in Table 3 (i.e., the CPI and PPI each interacted with luminosity in 1992, distance to the nearest "lit" cell in 1992, distance to nearest port, and distance to nearest border).

In the Column (1), we show that the PPI effect is -30.3% in cells that lacked a sophisticated jurisdictional hierarchy, and $-30.3 + 23.7 = -6.6\%$ in cells associated a higher degree of political centralization. The PPI effect is diminished by 80% where these "better" institutions were present. We also see a consistent result with respect to the CPI, where the effect is lower by -17.1% of the mean in cells with better institutions. Taken together, we see evidence that the impact of both price indices on factor conflict is closer to zero in cells with historically higher degrees of political centralization. In the second column, the point estimates of the interaction effects remain quite stable, but only the PPI interaction is significantly different to zero.

We repeat the exercise with output conflict as the dependent variable in Table A31. The interactions with the PPI are not significantly different to zero. This indicates that institutions (as they are measured here) play a role in mitigating large scale factor conflict battles, but not in mitigating output conflict events. While we did not have a strong prior on this effect, it is consistent with the idea that riots, theft or protests can be triggered by price shocks in many areas, but armed battles can only be triggered by prices shocks in areas with particularly dysfunctional institutions. Indeed, we see that in the interaction effect with the CPI is in fact positive, meaning that CPI shocks are more likely to lead to output conflict in these cells relative to cells without jurisdictional hierarchy beyond the local level. This could be due to the relative absence of factor conflict as an option for would-be fighters, who instead turn immediately to output conflict in the wake of price shocks. Or, it might simply reflect the fact that there is more to appropriate in these cells. Either way, it is clear that precolonial political centralization is associated with smaller PPI and CPI effects on factor conflict, but not output conflict.

Appendix Figures

Figure A1: **Temporal and spatial autocorrelation in prices**. Map at right shows an example of the 100km annuli (concentric circles) we use to calculate spatial autocorrelation, placed over an arbitrary location in Uganda. Annuli are re-calculated for every cell on the continent. We study impacts out to 500km from each cell; the diameter of the outer annulus (1000km) is roughly the width of Kenya.

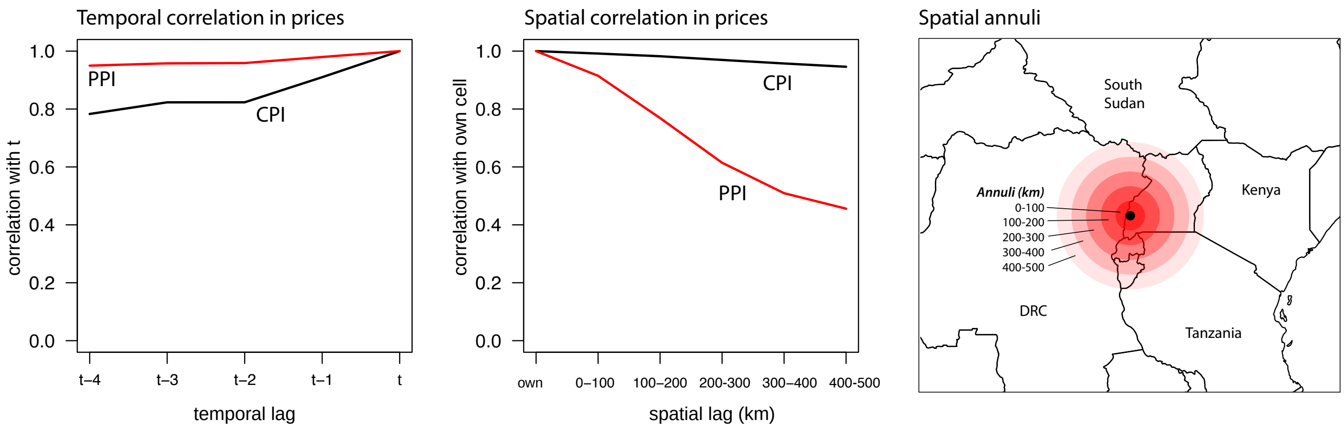


Figure A2: **Simulation of contemporaneous and lagged effects when independent variable is autocorrelated**. Dark black line shows "true" effect of contemporaneous or lagged independent variables on the outcome, grey lines are estimated effects for lags and leads (each line is one of 100 simulations). Cumulative effects of lags and leads are shown in small plots; black dot is true cumulative effect of lags ($\sum_{t-4}^{t} \beta_t = 15$) or leads ($\sum_{t+1}^{t+2} \beta_t = 0$), grey dots are estimated cumulative effects from simulations. Note different scale for these inset plots. Left plots: lower autocorrelation in the independent variables. Right plots: high autocorrelation.

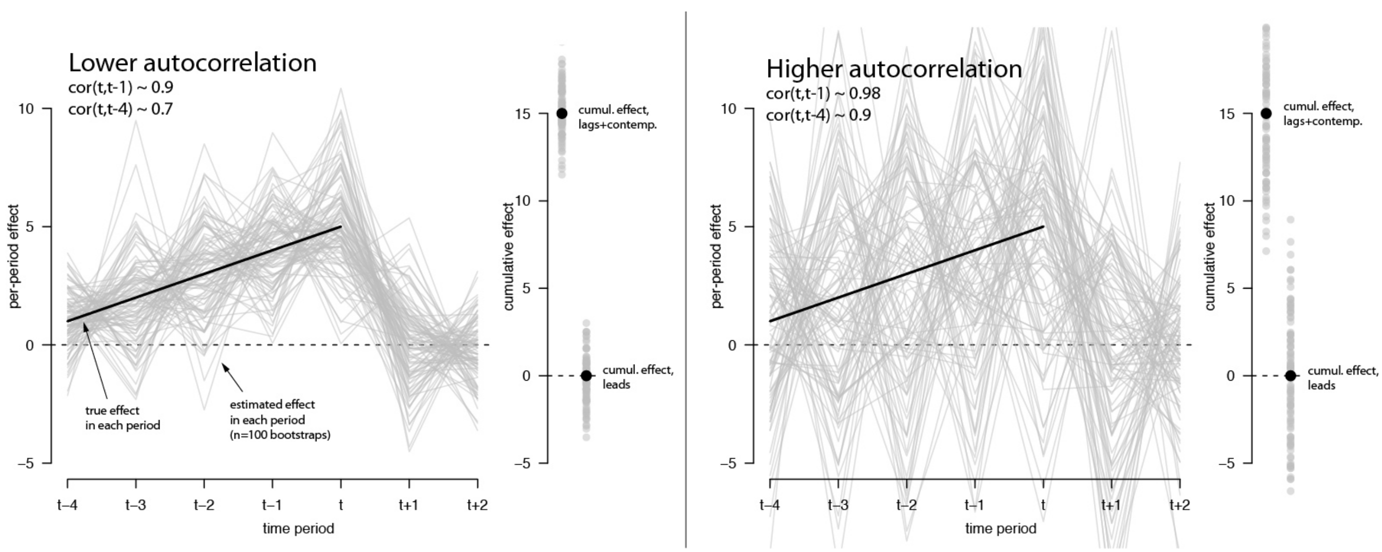


Figure A3: Cell Resolution

Note: each point is the centroid of a 0.5 $\times$ 0.5 degree cell.

Figure A4: FAO Global Food Price Index Series from 1990-2013

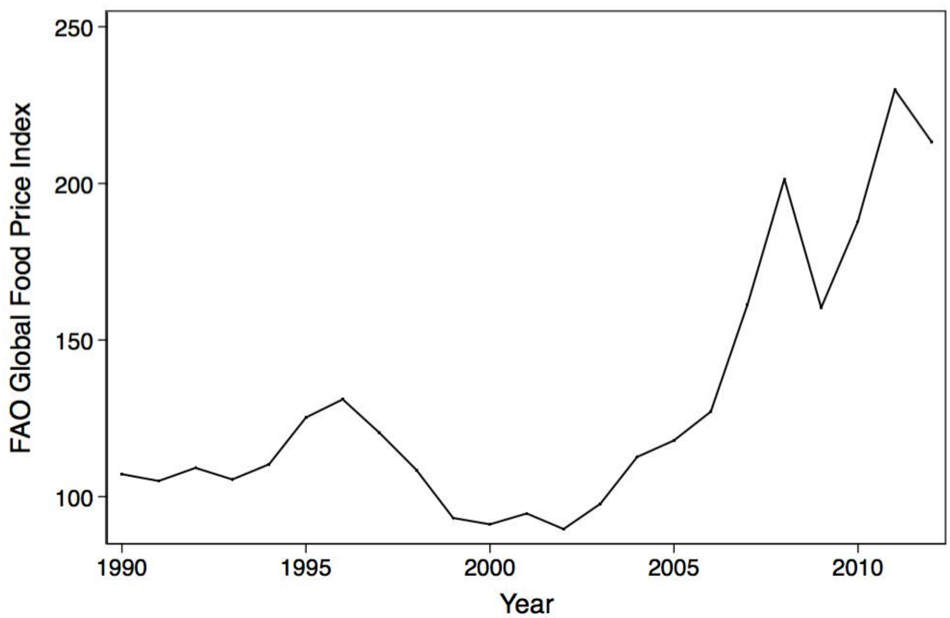


Figure A5: Crop Price Probability Density Functions (Kernel Estimation)

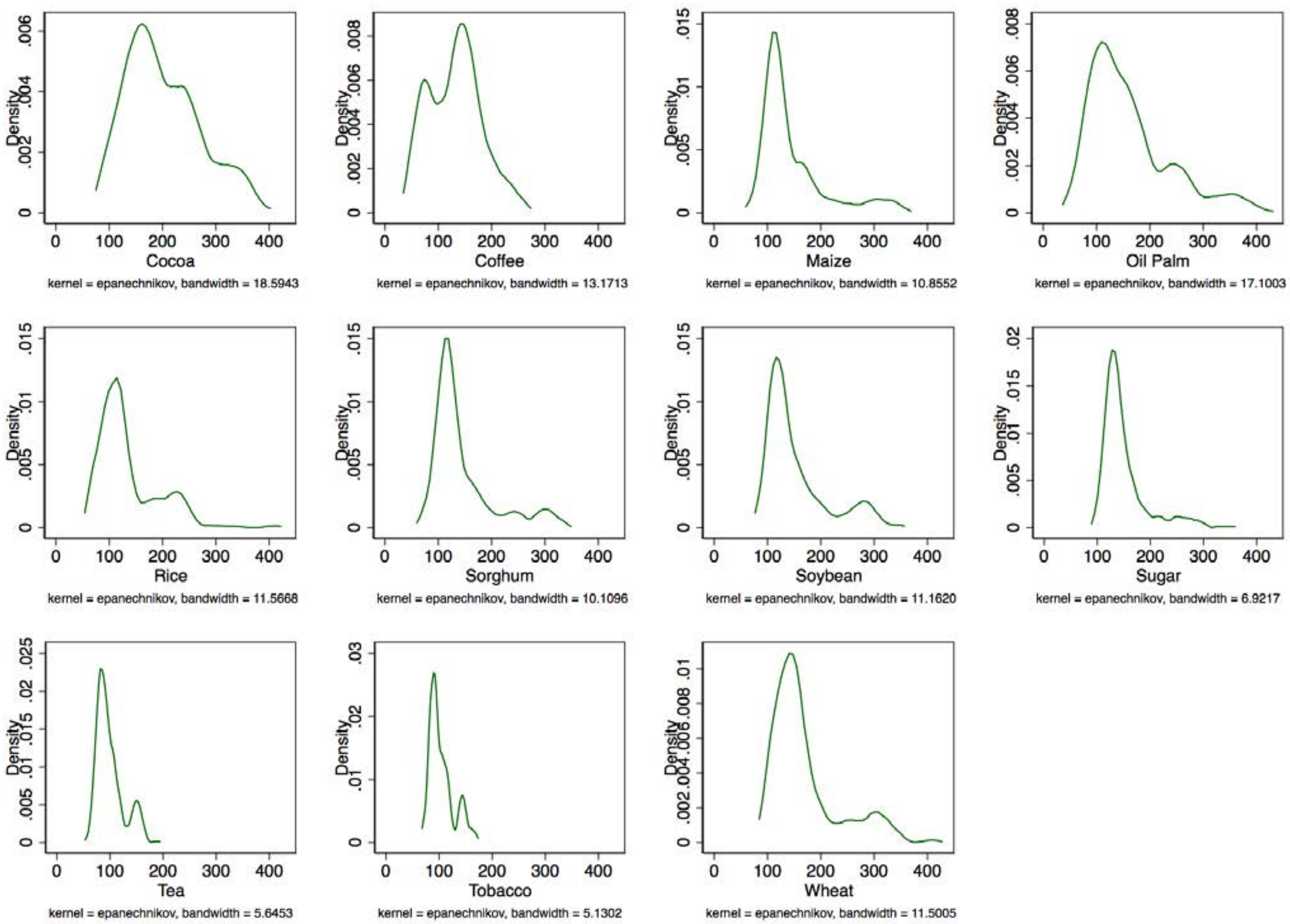
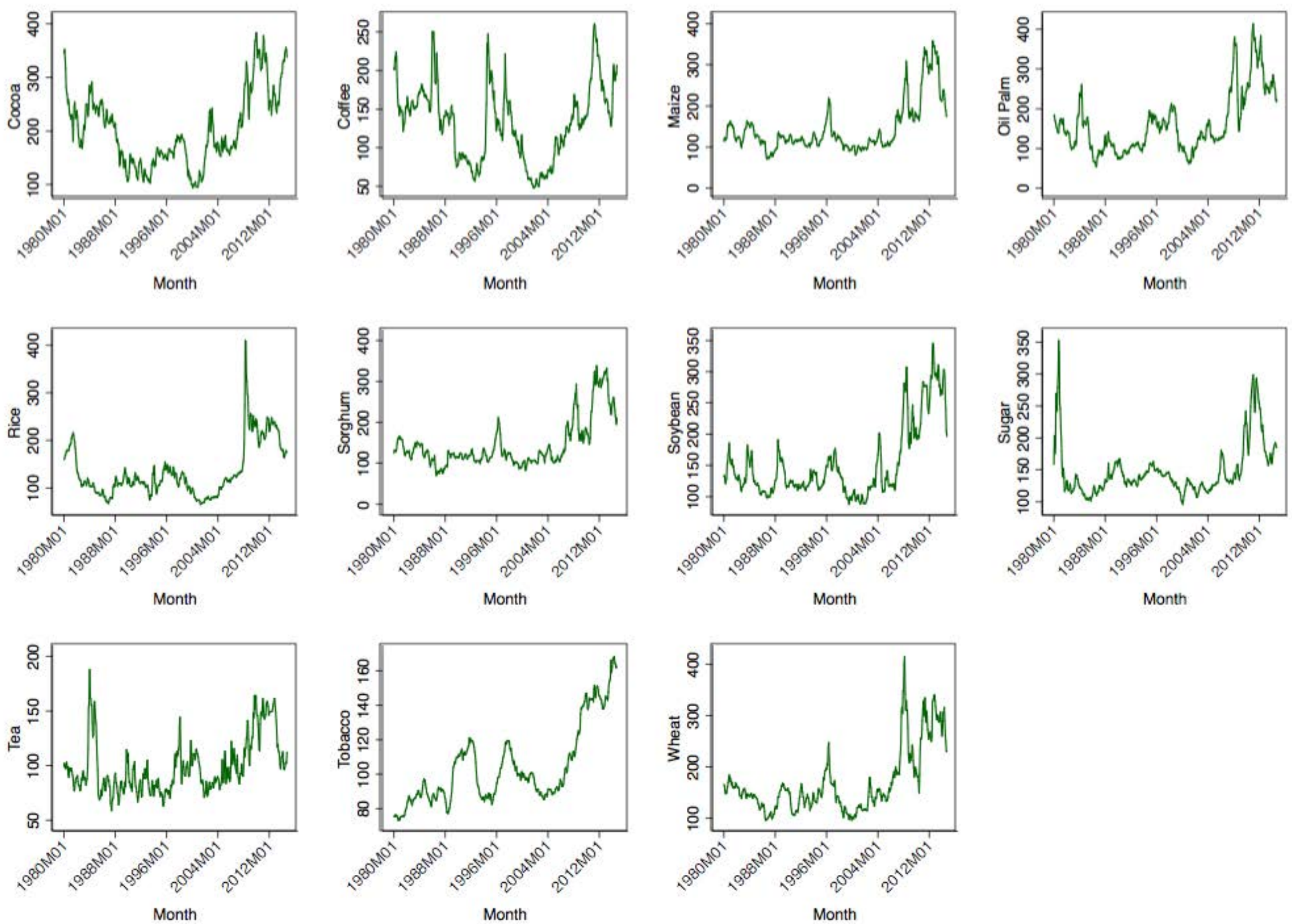


Figure A6: Crop Price Monthly Series (2000M01 = 100)



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 Year Fixed Effects and Added Controls

	Incidence 1(Conflict > 0)			Onset 1(Conflict Begins)			Offset 1(Conflict Ends)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Producer Price Index	-0.0043	-0.0044	-0.0058	-0.0027	-0.0027	-0.0034	0.0385	0.0388	0.0553
Conley SE	0.001	0.001	0.001	0.001	0.001	0.001	0.016	0.016	0.015
p-value	0.000	0.000	0.000	0.002	0.002	0.001	0.018	0.017	0.000
Two-way SE	0.001	0.001	0.002	0.001	0.001	0.001	0.020	0.021	0.020
p-value	0.002	0.003	0.001	0.012	0.013	0.003	0.060	0.060	0.007
Consumer Price Index	0.0064	0.0083	0.0176	0.0054	0.0069	0.0059	-0.1066	-0.1255	-0.0969
Conley SE	0.005	0.005	0.008	0.003	0.003	0.005	0.080	0.080	0.143
p-value	0.189	0.101	0.025	0.072	0.026	0.260	0.180	0.117	0.498
Two-way SE	0.006	0.006	0.010	0.004	0.004	0.005	0.092	0.093	0.195
p-value	0.319	0.203	0.066	0.138	0.068	0.279	0.248	0.178	0.619
PPI impact (%)	-16.1	-16.3	-21.6	-18.7	-18.6	-23.6	7.2	7.3	10.3
CPI impact (%)	23.7	30.6	65.0	37.7	48.1	40.8	-19.9	-23.5	-18.1
Wald test: PPI = CPI									
Conley p-value	0.029	0.013	0.003	0.009	0.003	0.082	0.077	0.045	0.284
Two-way p-value	0.097	0.053	0.017	0.035	0.015	0.096	0.135	0.091	0.439
Mine controls	No	No	Yes	No	No	Yes	No	No	Yes
Weather controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Oil controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	204820	204490	110880	202297	201967	109593	4631	4629	2301

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 average temporal standard deviations. The coefficients displayed capture the sum of price impacts at t, t-1 and t-2. Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way 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. Weather controls are measured at the cell-level, and include *Temperature*, the cell-year mean temperature in degrees celsius; *moderate drought*, which 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*, which 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*, which indicates that both of these criteria were met in a cell-year. Oil controls include interactions between the world oil price and *Oil cell*, a dummy indicating the presence of an oil field in a given cell, and *oil country*, a dummy indicating that there is an oil field in a given country. Mine controls are taken from Berman et al. (2017), and include a dummy for whether or not there is an active mine in the cell, the log of the price for the main mineral produced in a cell over the sample period, and an interaction term.

Table A3: UCDP Factor Conflict: Two-Sided Violence Only

	Incidence 1(Conflict > 0)	Onset 1(Conflict Begins)	Offset 1(Conflict Ends)
	(1)	(2)	(3)
Producer Price Index	-0.0043	-0.0028	0.0603
SE	0.001	0.001	0.028
p-value	0.001	0.003	0.033
Consumer Price Index	0.0017	0.0011	-0.0933
SE	0.001	0.001	0.029
p-value	0.152	0.194	0.001
PPI impact (%)	-20.7	-24.6	10.9
CPI impact (%)	8.4	9.6	-16.8
Wald test: PPI = CPI			
p-value	0.000	0.001	0.001
Trade weight	No	No	No
Country × time trend	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes
Observations	204820	202893	3615

Note: The dependent variables are incidence, onset and offset dummies for the two-sided violence component of UCDP Factor Conflict. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured respectively in terms of average temporal standard deviations. The coefficients displayed capture the sum of price impacts at t, t-1 and t-2. 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 A4: UCDP Factor Conflict: Sensitivity of Standard Errors

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	-0.0042	-0.0046	-0.0024	-0.0029	0.0443	0.0494
100km SE	0.001	0.001	0.001	0.001	0.016	0.016
p-value	0.000	0.000	0.000	0.000	0.007	0.002
200km SE	0.001	0.001	0.001	0.001	0.016	0.018
p-value	0.000	0.000	0.001	0.001	0.007	0.005
300km SE	0.001	0.001	0.001	0.001	0.017	0.018
p-value	0.000	0.000	0.002	0.003	0.009	0.007
400km SE	0.001	0.001	0.001	0.001	0.017	0.019
p-value	0.000	0.000	0.003	0.003	0.011	0.008
500km SE	0.001	0.001	0.001	0.001	0.018	0.019
p-value	0.000	0.000	0.004	0.005	0.013	0.009
600km SE	0.001	0.001	0.001	0.001	0.018	0.019
p-value	0.000	0.000	0.005	0.005	0.015	0.011
700km SE	0.001	0.001	0.001	0.001	0.019	0.020
p-value	0.001	0.000	0.006	0.006	0.017	0.015
800km SE	0.001	0.001	0.001	0.001	0.019	0.022
p-value	0.001	0.000	0.007	0.008	0.020	0.023
900km SE	0.001	0.001	0.001	0.001	0.019	0.022
p-value	0.001	0.000	0.008	0.008	0.022	0.024
1000km SE	0.001	0.001	0.001	0.001	0.020	0.022
p-value	0.001	0.000	0.009	0.008	0.023	0.023
Consumer Price Index		0.0023		0.0015		-0.0881
100km SE		0.001		0.001		0.018
p-value		0.005		0.015		0.000
200km SE		0.001		0.001		0.020
p-value		0.047		0.064		0.000
300km SE		0.001		0.001		0.022
p-value		0.087		0.105		0.000
400km SE		0.001		0.001		0.023
p-value		0.114		0.133		0.000
500km SE		0.002		0.001		0.023
p-value		0.127		0.149		0.000
600km SE		0.002		0.001		0.023
p-value		0.134		0.164		0.000
700km SE		0.002		0.001		0.024
p-value		0.137		0.176		0.000
800km SE		0.002		0.001		0.024
p-value		0.134		0.177		0.000
900km SE		0.002		0.001		0.024
p-value		0.129		0.180		0.000
1000km SE		0.002		0.001		0.025
p-value		0.126		0.179		0.000
Wald test: PPI = CPI						
100km p-value		0.000		0.000		0.000
200km p-value		0.000		0.000		0.000
300km p-value		0.000		0.001		0.000
400km p-value		0.000		0.002		0.000
500km p-value		0.000		0.002		0.000
600km p-value		0.000		0.002		0.000
700km p-value		0.000		0.003		0.000
800km p-value		0.000		0.003		0.000
900km p-value		0.000		0.003		0.000
1000km p-value		0.000		0.003		0.000
Country × year FE	Yes	No	Yes	No	Yes	No
Country × time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225038	204820	222159	202298	6083	5352

Note: Conley standard errors allow for serial and spatial correlation within a given radius.

Table A5: UCDP Factor Conflict: One Degree Aggregation

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	-0.0093	-0.0044	-0.0063	-0.0035	0.0132	0.0187
Conley SE	0.003	0.003	0.002	0.003	0.022	0.016
p-value	0.000	0.180	0.006	0.245	0.549	0.230
Two-way SE	0.004	0.003	0.003	0.003	0.027	0.017
p-value	0.012	0.175	0.020	0.181	0.628	0.269
Consumer Price Index		-0.0025		0.0016		-0.1433
Conley SE		0.004		0.003		0.026
p-value		0.522		0.585		0.000
Two-way SE		0.004		0.003		0.027
p-value		0.552		0.592		0.000
PPI impact (%)	-12.9	-6.1	-13.9	-7.7	2.1	2.9
CPI impact (%)		-3.5		3.6		-22.3
Wald test: PPI = CPI						
p-value		0.749		0.230		0.000
Country × year FE	Yes	No	Yes	No	Yes	No
Country × time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58446	54032	58317	53909	3720	3578

Note: Blah.

Table A6: UCDP Factor Conflict: One Degree Aggregation with Spatial Weights

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	-0.0075	-0.0064	-0.0051	-0.0046	0.0153	0.0291
Conley SE	0.003	0.003	0.003	0.003	0.027	0.027
p-value	0.022	0.063	0.084	0.115	0.574	0.280
Two-way SE	0.004	0.004	0.003	0.003	0.030	0.031
p-value	0.050	0.082	0.062	0.072	0.615	0.346
Producer Price Index in neighboring cells	-0.0023	0.0024	-0.0016	0.0013	0.0018	-0.0084
Conley SE	0.005	0.006	0.005	0.005	0.025	0.029
p-value	0.673	0.685	0.723	0.795	0.944	0.771
Two-way SE	0.006	0.005	0.004	0.004	0.026	0.030
p-value	0.691	0.637	0.709	0.760	0.946	0.782
Consumer Price Index		-0.0029		0.0014		-0.1443
Conley SE		0.004		0.003		0.026
p-value		0.483		0.654		0.000
Two-way SE		0.004		0.003		0.029
p-value		0.507		0.651		0.000
PPI impact (%)	-10.6	-9.0	-11.4	-10.3	2.4	4.5
PPI impact in neighboring cells (%)	-3.2	3.4	-3.7	2.8	0.3	-1.3
CPI impact (%)		-4.0		3.1		-22.5
Wald test: PPI = CPI						
p-value		0.555		0.148		0.000
Country × year FE	Yes	No	Yes	No	Yes	No
Country × time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.409	0.326	0.246	0.169	0.429	0.294
Observations	53968	54010	53844	53887	3404	3571

Note: Blah.

Table A7: UCDP Factor Conflict with Control for Population

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	-0.0041	-0.0046	-0.0023	-0.0028	0.0452	0.0498
SE	0.002	0.001	0.001	0.001	0.022	0.022
p-value	0.007	0.001	0.020	0.007	0.038	0.026
Consumer Price Index		0.0023		0.0015		-0.0865
SE		0.001		0.001		0.026
p-value		0.119		0.140		0.001
ln Population	-0.0108	0.0004	-0.0017	0.0067	-0.0327	0.2151
SE	0.009	0.009	0.005	0.005	0.244	0.198
p-value	0.236	0.968	0.704	0.147	0.893	0.277
PPI impact (%)	-15.3	-17.2	-16.2	-19.6	8.5	9.3
CPI impact (%)		8.6		10.7		-16.2
Wald test: PPI = CPI						
p-value		0.000		0.002		0.001
Country × Year FE	Yes	No	Yes	No	Yes	No
Country × time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	224158	203962	221276	201441	5104	4627

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 respectively in terms of average temporal standard deviations. The coefficients displayed capture the sum of price impacts at t, t-1 and t-2. 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. *Ln Population* varies at the cell-year level.

Table A8: UCDP Factor Conflict: Conditional Fixed Effects Logit

	Incidence 1(Conflict > 0)	Onset 1(Conflict Begins)	Offset 1(Conflict Ends)
	(1)	(2)	(3)
Producer Price Index	-0.0871	-0.0823	0.3461
SE	0.089	0.055	0.117
p-value	0.328	0.136	0.003
Consumer Price Index	-0.0132	-0.0102	-0.7986
SE	0.120	0.116	0.143
p-value	0.913	0.930	0.000
Wald test: PPI = CPI			
p-value	0.671	0.629	0.000
Time trend	Yes	Yes	Yes
Cell fixed effects	Yes	Yes	Yes
Pseudo-R squared	0.002	0.003	0.033
Observations	37268	32532	3907

Note: All regressions are estimated with a conditional 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 average temporal standard deviations. The coefficients displayed capture the sum of price impacts at t, t-1 and t-2. Standard errors allow for serial and spatial correlation at the country level.

Table A9: UCDP Factor Conflict with Trade Weights on Price Indices

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	-0.0050	-0.0059	-0.0025	-0.0027	0.0441	0.0391
SE	0.002	0.002	0.001	0.001	0.017	0.015
p-value	0.010	0.006	0.045	0.050	0.009	0.008
Consumer Price Index	0.0016	0.0014	0.0011	0.0009	-0.0730	-0.0659
SE	0.001	0.001	0.001	0.001	0.030	0.028
p-value	0.209	0.237	0.231	0.315	0.015	0.017
PPI impact (%)	-18.6	-21.8	-17.2	-18.5	8.2	7.3
CPI impact (%)	6.0	5.1	7.8	5.9	-13.7	-12.3
Wald test: PPI = CPI						
p-value	0.000	0.000	0.001	0.001	0.007	0.007
Trade weight	Avg	BL 1988	Avg	BL 1988	Avg	BL 1988
Country × time trend	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	204666	204666	202151	202151	4614	4614

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 respectively in terms of average temporal standard deviations. Both are weighted by the extent to which the component crops are traded internationally. Trade weights are defined as the sum of imports and exports divided by total domestic production for a given crop. In columns (1), (3) and (5), the trade weights are averaged over our entire sample period. In columns (2), (4) and (6), the are measured at baseline (1988). In both cases they are Winsorized to form a time invariant weight varying from 0 to 1. Trade and production statistics are taken from the FAO Statistics Division, accessible at http://faostat3.fao.org/home/E as at August 30th, 2015. The coefficients displayed capture the sum of price impacts at t, t-1 and t-2. 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 A10: UCDP Factor Conflict with Yield Weights on PPI

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index × Yield	-0.0007	-0.0012	-0.0007	-0.0011	0.0431	0.0308
Conley SE	0.001	0.001	0.000	0.001	0.023	0.020
p-value	0.276	0.145	0.146	0.110	0.066	0.126
Two-way SE	0.001	0.001	0.001	0.001	0.028	0.021
p-value	0.371	0.163	0.240	0.131	0.120	0.135
Consumer Price Index		0.0011		0.0008		-0.0635
Conley SE		0.002		0.001		0.023
p-value		0.505		0.471		0.006
Two-way SE		0.002		0.001		0.025
p-value		0.494		0.488		0.013
PPI impact (%)	-2.5	-4.5	-4.5	-7.9	8.1	5.8
CPI impact (%)		3.9		5.3		-11.9
Wald test: PPI = CPI						
Two-way p-value		0.192		0.143		0.009
Conley p-value		0.191		0.123		0.005
Country × year FE	Yes	No	Yes	No	Yes	No
Country × time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225016	204820	222132	202297	5108	4631

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 respectively in terms of average temporal standard deviations. *Producer Price Index × Yield* further weights each component crop by its estimated yield per hectare. The coefficients displayed capture the sum of price impacts at t, t-1 and t-2. Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way 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 A11: UCDP Factor Conflict without Lags

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	-0.0035	-0.0040	-0.0021	-0.0024	0.0221	0.0134
Two-way SE	0.001	0.001	0.001	0.001	0.017	0.016
p-value	0.003	0.000	0.008	0.001	0.189	0.393
Consumer Price Index		0.0018		0.0004		-0.0031
Two-way SE		0.001		0.001		0.023
p-value		0.180		0.693		0.890
PPI impact (%)	-12.9	-14.6	-14.3	-16.6	4.1	2.5
CPI impact (%)		6.6		2.6		-0.6
Wald test: PPI = CPI						
p-value		0.000		0.014		0.620
Country × year FE	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225016	204820	222132	202297	5108	4631

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 respectively in terms of average temporal standard deviations. 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 A12: ACLED Output Conflict with Year Fixed Effects and Added Controls

	Incidence 1(Conflict > 0)			Onset 1(Conflict Begins)			Offset 1(Conflict Ends)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Producer Price Index	0.0090	0.0082	0.0046	0.0078	0.0073	0.0056	0.0057	0.0051	0.0205
Conley SE	0.002	0.002	0.002	0.002	0.002	0.003	0.004	0.004	0.005
p-value	0.000	0.000	0.060	0.000	0.000	0.035	0.126	0.167	0.000
Two-way SE	0.003	0.003	0.003	0.002	0.002	0.003	0.005	0.005	0.007
p-value	0.001	0.001	0.107	0.000	0.001	0.040	0.236	0.274	0.002
Consumer Price Index	0.0013	0.0014	-0.0002	0.0024	0.0016	-0.0048	0.0064	0.0005	-0.2591
Conley SE	0.006	0.006	0.007	0.004	0.004	0.006	0.042	0.042	0.079
p-value	0.812	0.800	0.973	0.592	0.716	0.398	0.880	0.990	0.001
Two-way SE	0.008	0.008	0.009	0.006	0.006	0.006	0.050	0.049	0.092
p-value	0.864	0.853	0.978	0.704	0.794	0.451	0.898	0.992	0.005
PPI impact (%)	17.8	16.3	9.2	27.4	25.8	19.6	1.3	1.1	4.5
CPI impact (%)	2.6	2.8	-0.5	8.4	5.7	-16.8	1.4	0.1	-57.3
Mine controls	No	No	Yes	No	No	Yes	No	No	Yes
Weather controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Oil controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	158270	158015	110880	154795	154542	108945	6774	6765	3711

Note: The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured in terms of average temporal standard deviations. The coefficients displayed capture the sum of price impacts at t, t-1 and t-2. Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way 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. Weather controls are measured at the cell-level, and include *Temperature*, the cell-year mean temperature in degrees celsius; *moderate drought*, which 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*, which 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*, which indicates that both of these criteria were met in a cell-year. Oil controls include interactions between the world oil price and *Oil cell*, a dummy indicating the presence of an oil field in a given cell, and *oil country*, a dummy indicating that there is an oil field in a given country. Mine controls are taken from Berman et al. (2017), and include a dummy for whether or not there is an active mine in the cell, the log of the price for the main mineral produced in a cell over the sample period, and an interaction term.

Table A13: ACLED Output Conflict with Added Controls

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	0.0086	0.0047	0.0075	0.0056	0.0050	0.0187
Two-way SE	0.003	0.003	0.002	0.003	0.005	0.007
p-value	0.001	0.096	0.001	0.037	0.355	0.005
Consumer Price Index	0.0107	0.0001	0.0061	-0.0023	-0.1318	-0.2173
Two-way SE	0.004	0.007	0.004	0.005	0.031	0.074
p-value	0.015	0.989	0.098	0.651	0.000	0.003
PPI impact (%)	17.2	9.4	26.4	19.7	1.1	4.1
CPI impact (%)	21.3	0.2	21.6	-8.2	-29.2	-48.1
Mine controls	No	Yes	No	Yes	No	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Oil controls	Yes	Yes	Yes	Yes	Yes	Yes
Country × time trend	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	158015	110880	154543	108948	7800	4538

Note: The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured in terms of average temporal standard deviations. The coefficients displayed capture the sum of price impacts at t, t-1 and t-2. Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way 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. Weather controls are measured at the cell-level, and include *Temperature*, the cell-year mean temperature in degrees celsius; *moderate drought*, which 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*, which 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*, which indicates that both of these criteria were met in a cell-year. Oil controls include interactions between the world oil price and *oil cell*, a dummy indicating the presence of an oil field in a given cell, and *oil country*, a dummy indicating that there is an oil field in a given country. Mine controls are taken from Berman et al. (2017), and include a dummy for whether or not there is an active mine in the cell, the log of the price for the main mineral produced in a cell over the sample period, and an interaction term between the two.

Table A14: ACLED Output Conflict, Riots Only

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	0.0105	0.0110	0.0086	0.0084	0.0108	0.0074
Two-way SE	0.002	0.002	0.002	0.002	0.004	0.006
p-value	0.000	0.000	0.000	0.000	0.006	0.204
Consumer Price Index		0.0057		0.0026		-0.1550
Two-way SE		0.001		0.001		0.022
p-value		0.000		0.019		0.000
PPI impact (%)	48.7	51.0	64.1	62.9	2.3	1.6
CPI impact (%)		26.5		19.2		-33.1
Country $\times$ year FE	Yes	No	Yes	No	Yes	No
Country $\times$ time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	173876	158270	172443	156940	2698	2762

Table A15: ACLED Output Conflict: Sensitivity of Standard Errors

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	0.0076	0.0095	0.0068	0.0080	0.0092	0.0069
100km SE	0.001	0.001	0.001	0.001	0.002	0.004
p-value	0.000	0.000	0.000	0.000	0.000	0.076
200km SE	0.002	0.002	0.002	0.002	0.003	0.005
p-value	0.000	0.000	0.000	0.000	0.001	0.156
300km SE	0.002	0.002	0.002	0.002	0.003	0.005
p-value	0.000	0.000	0.000	0.000	0.001	0.178
400km SE	0.002	0.002	0.002	0.002	0.003	0.005
p-value	0.000	0.000	0.000	0.000	0.001	0.190
500km SE	0.002	0.002	0.002	0.002	0.003	0.005
p-value	0.000	0.000	0.000	0.000	0.002	0.207
600km SE	0.002	0.002	0.002	0.002	0.003	0.005
p-value	0.000	0.000	0.001	0.001	0.003	0.204
700km SE	0.002	0.002	0.002	0.002	0.003	0.005
p-value	0.000	0.000	0.001	0.001	0.004	0.207
800km SE	0.002	0.002	0.002	0.002	0.003	0.005
p-value	0.000	0.000	0.001	0.001	0.005	0.207
900km SE	0.002	0.002	0.002	0.002	0.003	0.005
p-value	0.001	0.000	0.002	0.001	0.005	0.206
1000km SE	0.002	0.002	0.002	0.002	0.003	0.005
p-value	0.001	0.000	0.002	0.001	0.006	0.208
Consumer Price Index		0.0072		0.0033		-0.1271
100km SE		0.001		0.001		0.014
p-value		0.000		0.000		0.000
200km SE		0.001		0.001		0.012
p-value		0.000		0.000		0.000
300km SE		0.001		0.001		0.016
p-value		0.000		0.003		0.000
400km SE		0.002		0.001		0.016
p-value		0.000		0.006		0.000
500km SE		0.002		0.001		0.017
p-value		0.000		0.010		0.000
600km SE		0.002		0.001		0.017
p-value		0.000		0.015		0.000
700km SE		0.002		0.001		0.017
p-value		0.000		0.022		0.000
800km SE		0.002		0.002		0.017
p-value		0.000		0.029		0.000
900km SE		0.002		0.002		0.018
p-value		0.000		0.035		0.000
1000km SE		0.002		0.002		0.018
p-value		0.000		0.041		0.000
Country × year FE	Yes	No	Yes	No	Yes	No
Country × time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	173893	158270	169953	154796	8762	7810

Note: Conley standard errors allow for serial and spatial correlation within a given radius.

Table A16: ACLED Output Conflict: One Degree Aggregation

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	0.0045	0.0166	0.0103	0.0203	0.0083	0.0059
Conley SE	0.003	0.004	0.003	0.004	0.004	0.008
p-value	0.136	0.000	0.001	0.000	0.029	0.441
Two-way SE	0.005	0.004	0.004	0.004	0.005	0.007
p-value	0.351	0.000	0.012	0.000	0.109	0.429
Consumer Price Index		0.0371		0.0235		-0.1308
Conley SE		0.004		0.003		0.016
p-value		0.000		0.000		0.000
Two-way SE		0.005		0.003		0.017
p-value		0.000		0.000		0.000
PPI impact (%)	3.3	12.0	11.5	22.6	1.5	1.1
CPI impact (%)		26.8		26.2		-23.9
Wald test: PPI = CPI						
p-value		0.003		0.594		0.000
Country × year FE	Yes	No	Yes	No	Yes	No
Country × time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45162	41752	45052	41661	5716	5412

Note: Blah.

Table A17: ACLED Output Conflict: One Degree Aggregation with Spatial Weight

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	0.0056	0.0053	0.0111	0.0110	-0.0041	0.0009
Conley SE	0.003	0.003	0.004	0.004	0.004	0.005
p-value	0.097	0.099	0.006	0.003	0.361	0.847
Two-way SE	0.005	0.005	0.004	0.004	0.006	0.005
p-value	0.291	0.321	0.007	0.007	0.475	0.869
Producer Price Index in neighboring cells	-0.0005	0.0147	0.0009	0.0123	0.0268	0.0055
Conley SE	0.005	0.005	0.005	0.006	0.007	0.013
p-value	0.918	0.003	0.854	0.029	0.000	0.664
Two-way SE	0.007	0.006	0.006	0.006	0.011	0.014
p-value	0.947	0.021	0.872	0.046	0.015	0.692
Consumer Price Index		0.0348		0.0218		-0.1615
Conley SE		0.004		0.003		0.014
p-value		0.000		0.000		0.000
Two-way SE		0.005		0.004		0.015
p-value		0.000		0.000		0.000
PPI impact (%)	4.0	3.9	12.5	12.3	-0.7	0.2
PPI impact in neighboring cells (%)	-0.3	10.7	1.1	13.8	4.9	1.0
CPI impact (%)		25.3		24.4		-29.5
Wald test: PPI = CPI						
p-value		0.000		0.062		0.000
Country × year FE	Yes	No	Yes	No	Yes	No
Country × time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.487	0.424	0.284	0.213	0.495	0.339
Observations	41701	41735	41608	41644	5240	5407

Note: Blah.

Table A18: ACLED Output Conflict with Control for Population

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	0.0076	0.0093	0.0068	0.0079	0.0092	0.0074
SE	0.003	0.003	0.002	0.002	0.005	0.006
p-value	0.007	0.000	0.004	0.000	0.049	0.207
Consumer Price Index		0.0066		0.0031		-0.1026
SE		0.002		0.001		0.021
p-value		0.000		0.023		0.000
ln Population	0.0026	-0.0491	-0.0011	-0.0175	0.2891	0.7885
SE	0.017	0.017	0.011	0.012	0.248	0.245
p-value	0.881	0.005	0.917	0.161	0.244	0.001
PPI impact (%)	15.1	18.5	23.9	28.0	2.0	1.6
CPI impact (%)		13.0		10.9		-22.7
Country × Year FE	Yes	No	Yes	No	Yes	No
Country × time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	173213	157607	169275	154137	7403	6767

Note: The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured respectively in terms of average temporal standard deviations. The coefficients displayed capture the sum of price impacts at t, t-1 and t-2. 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. *Ln Population* varies at the cell-year level.

Table A19: ACLED Output Conflict: Conditional Logit

	Incidence 1(Conflict > 0)	Onset 1(Conflict Begins)	Offset 1(Conflict Ends)
	(1)	(2)	(3)
Producer Price Index: Food crops	0.0292	0.0304	-0.0000
SE	0.020	0.019	0.016
p-value	0.139	0.107	0.998
Producer Price Index: Cash crops	-0.0221	-0.0161	0.0492
SE	0.021	0.019	0.020
p-value	0.301	0.394	0.013
Consumer Price Index	0.3646	0.1572	-0.6686
SE	0.150	0.106	0.170
p-value	0.015	0.138	0.000
Wald test: PPI food = PPI Cash			
p-value	0.073	0.114	0.035
Time trend	Yes	Yes	Yes
Cell fixed effects	Yes	Yes	Yes
Pseudo-R squared	0.063	0.058	0.148
Observations	42092	37870	5462

Note: All regressions are estimated with a conditional logit estimator. The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured in terms of average temporal standard deviations. The coefficients displayed capture the sum of price impacts at t, t-1 and t-2. *Food crops* are crops that each represent at least 1% of caloric intake in the sample; *cash crops* are the rest (see Table A1). Standard errors allow for serial and spatial correlation at the country level.

Table A20: ACLED Output Conflict with Trade Weights

	Incidence 1(Conflict $>$ 0)			Onset 1(Conflict Begins)			Offset 1(Conflict Ends)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Producer Price Index: Food crops	0.0084	0.0084	0.0073	0.0065	0.0062	0.0052	0.0083	0.0065	0.0075
SE	0.002	0.002	0.002	0.002	0.002	0.002	0.005	0.004	0.004
p-value	0.000	0.000	0.002	0.000	0.001	0.001	0.088	0.111	0.040
Producer Price Index: Cash crops	-0.0006	-0.0005	-0.0002	-0.0000	0.0002	0.0003	0.0092	0.0088	0.0073
SE	0.002	0.002	0.002	0.002	0.002	0.002	0.008	0.008	0.008
p-value	0.753	0.819	0.943	0.985	0.895	0.868	0.222	0.251	0.337
Consumer Price Index	0.0040	0.0039	0.0032	0.0018	0.0018	0.0015	-0.1037	-0.1022	-0.0996
SE	0.001	0.001	0.001	0.001	0.001	0.001	0.017	0.017	0.016
p-value	0.001	0.001	0.002	0.015	0.011	0.011	0.000	0.000	0.000
PPI impact: food (%)	16.6	16.6	14.5	23.0	21.8	18.3	1.8	1.4	1.7
PPI impact: cash (%)	-1.2	-0.9	-0.3	-0.1	0.8	1.1	2.0	1.9	1.6
CPI impact (%)	7.9	7.7	6.3	6.4	6.2	5.3	-23.0	-22.6	-22.0
Trade weight	Avg	BL 1996	BL 1988	Avg	BL 1996	BL 1988	Avg	BL 1996	BL 1988
Country × time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	158151	158151	158151	154677	154677	154677	6769	6769	6769

Note: The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured respectively in terms of average temporal standard deviations. Both are weighted by the extent to which the component crops are traded internationally. Trade weights are defined as the sum of imports and exports divided by total domestic production for a given crop. In columns (1), (3) and (5), the trade weights are averaged over our entire sample period. In columns (2), (4) and (6), the are measured at baseline (1988). In both cases they are Winsorized to form a time invariant weight varying from 0 to 1. Trade and production statistics are taken from the FAO Statistics Division, accessible at http://faostat3.fao.org/home/E as at August 30th, 2015. The coefficients displayed capture the sum of price impacts at t, t-1 and t-2. 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 A21: ACLED Output Conflict with Yield Weights on PPI

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index × Yield	0.0074	0.0082	0.0067	0.0073	0.0041	0.0030
Conley SE	0.002	0.002	0.002	0.003	0.002	0.004
p-value	0.000	0.000	0.001	0.004	0.053	0.411
Two-way SE	0.002	0.002	0.002	0.002	0.003	0.004
p-value	0.001	0.000	0.004	0.003	0.164	0.420
Consumer Price Index		0.0088		0.0045		-0.1215
Conley SE		0.002		0.001		0.016
p-value		0.000		0.001		0.000
Two-way SE		0.002		0.001		0.018
p-value		0.000		0.001		0.000
PPI impact (%)	14.7	16.2	23.5	25.8	0.9	0.7
CPI impact (%)		17.4		15.8		-26.9
Country × year FE	Yes	No	Yes	No	Yes	No
Country × time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	173876	158270	169933	154795	7410	6774

Note: The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured respectively in terms of average temporal standard deviations. *Producer Price Index × Yield* further weights each component crop by its estimated yield per hectare. The coefficients displayed capture the sum of price impacts at t, t-1 and t-2. Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way 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 A22: ACLED Output Conflict without Lags

	Incidence 1(Conflict > 0)		Onset 1(Conflict Begins)		Offset 1(Conflict Ends)	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index: Food crops	0.0058	0.0066	0.0057	0.0061	0.0059	0.0018
Two-way SE	0.002	0.002	0.002	0.002	0.003	0.004
p-value	0.006	0.005	0.001	0.001	0.075	0.670
Producer Price Index: Cash crops	-0.0015	-0.0023	-0.0010	-0.0015	0.0128	0.0142
Two-way SE	0.002	0.002	0.002	0.001	0.007	0.007
p-value	0.420	0.152	0.511	0.282	0.065	0.038
Consumer Price Index		0.0036		0.0019		-0.0444
Two-way SE		0.002		0.001		0.016
p-value		0.042		0.170		0.006
PPI impact: food (%)	11.6	13.0	20.1	21.5	1.3	0.4
PPI impact: cash (%)	-3.0	-4.5	-2.0	-3.0	25.5	28.1
CPI impact (%)		7.2		6.7		-9.8
Wald test: PPI food = PPI cash						
p-value	0.001	0.000	0.000	0.000	0.291	0.050
Country × year FE	Yes	No	Yes	No	Yes	no
Country × time trend	N/A	Yes	N/A	Yes	N/A	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	173876	158270	169933	154795	7410	6774

Note: The dependent variables are dummies for ACLED Output Conflict incidence, onset and offset dummies. The price indices are measured respectively in terms of sample average temporal 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 capture the sum of price impacts at t, t-1 and t-2. Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI impact* indicates the effect of a one standard deviation rise in prices on the outcome variable in percentage terms.

Table A23: ACLED Output Conflict, Producer Prices and Consumer Prices: Urban Riots

	ACLED Incidence: 1(Conflict > 0)			
	(1)	(2)	(3)	(4)
Producer Price Index: Food crops	0.0066	0.0044	0.0096	0.0076
SE	0.002	0.002	0.002	0.003
p-value	0.002	0.052	0.000	0.004
Producer Price Index: Cash crops	-0.0021	-0.0027	-0.0023	-0.0028
SE	0.002	0.002	0.002	0.002
p-value	0.275	0.214	0.240	0.197
Consumer Price Index	0.0056		0.0073	
SE	0.002		0.002	
p-value	0.001		0.000	
Consumer Price Index $\times$ urban area	0.2501	0.2526		
SE	0.043	0.042		
p-value	0.000	0.000		
Consumer Price Index $\times$ urban population			0.0000	0.0000
SE			0.000	0.000
p-value			0.138	0.119
CPI impact (%) at urban area = 0	11.1	0.0		
CPI impact (%) at urban area 90th pctile	20.0	9.0		
CPI impact (%) at urban pop = 0			14.6	0.0
CPI impact (%) at urban pop 90th pctile			15.2	0.6
Country $\times$ time trend	Yes	N/A	Yes	N/A
Country $\times$ year fixed effects	No	Yes	No	Yes
Cell FE	Yes	Yes	Yes	Yes
R squared	0.376	0.400	0.373	0.397
Observations	158168	158168	158270	158270

Note: The dependent variables are dummies for ACLED Output Conflict incidence, onset and offset dummies. The price indices are measured respectively in terms of sample average temporal 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 capture the sum of price impacts at t, t-1 and t-2. Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way standard errors allow for serial correlation within cells and spatial correlation across cells within countries. *PPI impact* indicates the effect of a one standard deviation rise in 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 A24: Comparison of Effects on Output Conflict and Factor Conflict Incidence

	UCDP Factor Conflict		ACLED Territorial Change		ACLED Output Conflict	
	(1)	(2)	(3)	(4)	(5)	(6)
Producer Price Index	-0.0046	-0.0050	-0.0001	-0.0006	0.0095	0.0045
Two-way SE	0.001	0.001	0.000	0.000	0.003	0.003
p-value	0.001	0.001	0.644	0.155	0.000	0.137
Consumer Price Index	0.0023	0.0012	0.0014	0.0007	0.0072	-0.0012
Two-way SE	0.001	0.002	0.001	0.001	0.002	0.002
p-value	0.116	0.481	0.015	0.215	0.000	0.462
PPI Impact	-17.2	-18.5	-2.6	-15.0	18.9	8.9
CPI impact (%)	8.6	4.4	33.2	17.0	14.4	-2.3
Wald test: PPI (total) = CPI						
p-value	0.000	0.002	0.007	0.038	0.498	0.125
Sample	1989-2010	1997-2010	1997-2013	1997-2010	1997-2013	1997-2010
Country × time trend	Yes	Yes	Yes	Yes	Yes	Yes
Cell fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	204820	130340	158270	130340	158270	130340

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) are measured respectively in terms of average temporal standard deviations. The coefficients displayed capture the sum of price impacts at t, t-1 and t-2. Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way 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 A25: Afrobarometer: Prices and Poverty

	Poverty: index			Poverty: income			Poverty: food		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Producer Price Index	0.0029	0.0019	0.0024	0.0016	0.0012	0.0006	0.0030	0.0025	0.0028
SE	0.001	0.002	0.003	0.001	0.001	0.002	0.001	0.001	0.003
p-value	0.026	0.335	0.354	0.041	0.256	0.756	0.016	0.093	0.263
Producer Price Index × farmer		-0.0023	-0.0020		-0.0004	-0.0003		-0.0009	-0.0010
SE		0.001	0.001		0.001	0.001		0.001	0.001
p-value		0.022	0.030		0.579	0.609		0.379	0.318
Consumer Price Index	0.0040			0.0025			0.0038		
SE	0.002			0.001			0.001		
p-value	0.025			0.029			0.003		
PPI impact (%)	0.6	0.4	0.5	0.3	0.2	0.1	0.9	0.7	0.8
PPI impact × farmer (%)		-0.5	-0.4		-0.1	-0.0		-0.3	-0.3
CPI impact (%)	0.9			0.4			1.1		
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
Observations	66946	41165	41153	66543	40892	40880	66836	41091	41079

Note: The dependent variables are 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 (67) have larger sample sizes as data on occupation is not available in all rounds. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured respectively in terms of average temporal 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 capture the sum of price impacts at t, t-1, t-2, t-3 and t-4, where each t is a six-month period. Standard errors allow for serial and spatial correlation within 1 degree cells. *PPI (CPI) Impact* indicates the effect of a one standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms.

Table A26: Afrobarometer: Prices and Poverty with Trade Weights

	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
Observations	66946	41133	41121	66543	40860	40848	66836	41059	41047

Note: The dependent variables are 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 (67) have larger sample sizes as data on occupation is not available in all rounds. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured respectively in terms of average temporal 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 capture the sum of price impacts at t, t-1, t-2, t-3 and t-4, where each t is a six-month period. Standard errors allow for serial and spatial correlation within 1 degree cells. *PPI (CPI) Impact* indicates the effect of a one standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms.

Table A27: 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 capture the sum of impacts over the previous year. Standard errors allow for serial and spatial correlation within 1 degree cells.

Table A28: Afrobarometer Output Conflict: Triple Difference with Trade Weights

	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	
Treatment effects				
(PPI Food − PPI Cash) × farmer	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
Impact on farmers (%)	14.3	16.2	19.1	16.3
(PPI Food − PPI Cash) × trader	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
Impact on traders (%)	15.1	13.6	6.4	4.5
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
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 terms of average temporal 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 capture the sum of price impacts at t, t-1, t-2, t-3 and t-4, 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 and spatial correlation within 1 degree cells. *PPI impact* indicates the effect of a one standard deviation rise in prices on the outcome variable in percentage terms.

Table A29: Afrobarometer Output Conflict: Triple Difference with Non-Commercial Farmer

	Theft		Violence	
	(1)	(2)	(3)	(4)
Producer Price Index: Food crops	0.0030	0.0018	-0.0002	-0.0005
SE	0.002	0.001	0.001	0.001
p-value	0.161	0.059	0.852	0.665
Producer Price Index: Food crops × non-commercial farmer	-0.0002	-0.0006	0.0008	0.0003
SE	0.001	0.001	0.001	0.001
p-value	0.828	0.592	0.427	0.673
Producer Price Index: Food crops × trader	0.0040	0.0045	0.0020	0.0023
SE	0.002	0.002	0.001	0.001
p-value	0.094	0.051	0.168	0.121
Producer Price Index: Cash crops	-0.0118	-0.0242	-0.0008	-0.0270
SE	0.013	0.016	0.010	0.007
p-value	0.358	0.141	0.937	0.000
Producer Price Index: Cash crops × non-commercial farmer	-0.0009	0.0001	0.0102	0.0066
SE	0.012	0.009	0.010	0.010
p-value	0.941	0.990	0.293	0.496
Producer Price Index: Cash crops × trader	-0.0234	-0.0156	-0.0063	-0.0041
SE	0.017	0.011	0.017	0.010
p-value	0.170	0.147	0.709	0.697
Consumer Price Index	0.0005		-0.0005	
SE	0.002		0.002	
p-value	0.806		0.758	
Treatment effects				
(PPI Food − PPI Cash) × non-commercial farmer	0.0006	-0.0007	-0.0094	-0.0063
SE	0.012	0.009	0.010	0.010
p-value	0.958	0.939	0.340	0.511
Impact on non-commercial farmers (%)	0.2	-0.2	-7.2	-4.8
(PPI Food − PPI Cash) × trader	0.0274	0.0201	0.0083	0.0063
SE	0.017	0.011	0.017	0.011
p-value	0.116	0.080	0.628	0.560
Impact on traders (%)	8.8	6.4	6.4	4.8
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
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 terms of average temporal 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 capture the sum of price impacts at t, t-1, t-2, t-3 and t-4, 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 and spatial correlation within 1 degree cells. *PPI impact* indicates the effect of a one standard deviation rise in prices on the outcome variable in percentage terms.

Table A30: UCDP Factor Conflict: Precolonial Institutions

	Incidence: $1(\text{Conflict} > 0)$	
	(1)	(2)
Producer Price Index	-0.0082	-0.0011
Conley SE	0.002	0.003
p-value	0.000	0.651
Two-way SE	0.003	0.003
p-value	0.003	0.721
Producer Price Index × Precolonial political centralization	0.0064	0.0060
Conley SE	0.002	0.002
p-value	0.001	0.007
Two-way SE	0.002	0.003
p-value	0.010	0.022
Consumer Price Index × Precolonial political centralization	-0.0046	-0.0036
Conley SE	0.002	0.003
p-value	0.055	0.152
Two-way SE	0.003	0.003
p-value	0.170	0.291
PPI impact (%)	-30.3	-4.2
PPI impact (%) × Precolonial political centralization	23.7	22.1
CPI impact (%) × Precolonial political centralization	-17.1	-13.3
Country × year FE	Yes	Yes
Cell FE	Yes	Yes
Extra Controls	No	Yes
Observations	203962	199430

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 respectively in terms of average temporal standard deviations. Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way 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. *Precolonial political centralization* is a proxy for institutional development, and is taken from Michalopoulos & Papaionnou (2013). It is equal to 1 if a cell is located in an ethnic territory in which the pre-colonial jurisdictional hierarchy went beyond the local level.

Table A31: ACLED Output Conflict: Precolonial Institutions

	Incidence: 1(Conflict > 0)	
	(1)	(2)
Producer Price Index: Food crops	0.0061	0.0037
Conley SE	0.003	0.003
p-value	0.016	0.259
Two-way SE	0.003	0.004
p-value	0.057	0.361
Producer Price Index: Food × Precolonial political centralization	0.0016	0.0000
Conley SE	0.002	0.002
p-value	0.528	0.987
Two-way SE	0.003	0.004
p-value	0.657	0.991
Producer Price Index: Cash crops	-0.0040	-0.0043
Conley SE	0.002	0.002
p-value	0.009	0.073
Two-way SE	0.002	0.003
p-value	0.039	0.173
Producer Price Index: Cash × Precolonial political centralization	0.0021	0.0014
Conley SE	0.002	0.002
p-value	0.269	0.439
Two-way SE	0.003	0.002
p-value	0.423	0.551
Consumer Price Index × Precolonial political centralization	0.0127	0.0113
Conley SE	0.002	0.002
p-value	0.000	0.000
Two-way SE	0.003	0.003
p-value	0.000	0.000
PPI impact: food (%)	12.1	7.3
PPI impact: food (%) × Precolonial political centralization	3.1	0.1
PPI impact: cash (%)	-8.0	-8.5
PPI impact: cash (%) × Precolonial political centralization	4.2	2.8
CPI impact (%) × Precolonial political centralization	25.3	22.5
Country × year FE	Yes	Yes
Cell FE	Yes	Yes
Extra Controls	No	Yes
Observations	157607	154105

Note: The dependent variables are ACLED Output Conflict incidence, onset and offset dummies. The *Producer Price Index* (PPI) and *Consumer Price Index* (CPI) are measured respectively in terms of average temporal 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). Conley standard errors allow for serial and spatial correlation within a radius of 500km. Two-way 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