The Economic Origins of Conflict in Africa

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We study the impact of global food price shocks on local violence across Africa. In food-producing areas, higher prices reduce conflict over the control of territory ("factor conflict") and increase conflict over the appropriation of surplus ("output conflict"). We argue that this difference arises because higher prices increase the opportunity cost of soldiering for producers while simultaneously inducing consumers to appropriate surplus as real wages fall. In areas without crop agriculture, higher prices increase both forms of conflict. We validate our local-level findings on output conflict using survey data. Our findings help reconcile a growing but ambiguous literature on the economic roots of conflict.

I. 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

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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.[2]

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.

Stephen Smith, Bryce Millett Steinberg, Chris Udry, Pedro Vicente, and Owen Zidar, as well as seminar/conference participants at the University of California (UC) Berkeley (Economics and Agricultural and Resource Economics), the World Bank (Development Research Group), PacDev (Pacific Development Conference; UC San Diego), the World Bank ABCA (Annual Bank Conference on Africa; UC Berkeley), the Watson Institute (Brown University), Yale University, Trinity College Dublin, and NEUDC (North East Universities Development Consortium; Brown University). All errors are ours. Data are provided as supplementary material online.

[1] See Abadie and Gardeazabal (2003), Collier et al. (2003), Ghobarah, Huth, and Russett (2003), and 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 from the UCDP GED data set (Sundberg and Melander 2013). At least 315,000 of these fatalities were civilians.

[2] For example, Djankov and Reynal-Querol (2010), Ciccone (2011), and Cotet and Tsui (2013) all challenge previously established associations between income and conflict.

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 as the opportunity cost of soldiering. 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° grid cell (around 55 km × 55 km at the equator) over the entire African continent. Data on factor conflict come from the Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED; Sundberg and Melander 2013), which includes geocoded conflict events that (1) feature at least one fatality and (2) 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 for each crop to form a cell-year measure. Controlling for both cell fixed effects and country-year fixed effects, we find that a 1 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. We posit that, through a negative effect on real income, food price spikes will cause those at low levels 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 United Nations Food and Agriculture Organization (UN 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. Because there is less cross-sectional variation in the composition of food consumed than in the composition of food produced, these estimates are typically not statistically significant when we include year fixed effects in our model.

The top 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 not only is important in its own right but 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

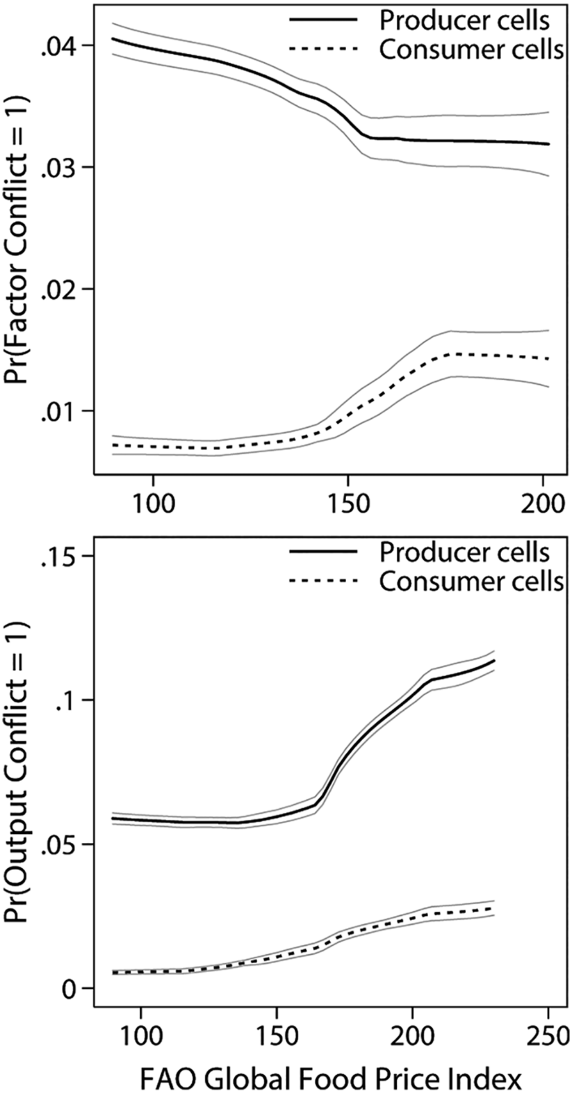

FIG. 1.—Factor conflict, output conflict, and FAO global food price index. Producer cells are cells where cropland area > 0. Consumer cells are cells where cropland area = 0. Factor Conflict is equal to 1 if any UCDP factor conflict events take place in a given cell-year and 0 otherwise. Output Conflict is equal to 1 if any ACLED (Armed Conflict Location and Event Dataset) output conflict events take place in a given cell-year and 0 otherwise. These data are introduced formally in section III. Epanechnikov kernel; bandwith = 20.

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 factor conflict from *output conflict*, which we define as a contest over the appropriation of surplus. Output 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 increase the value of appropriable output relative to real 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 bottom panel of figure 1 presents initial descriptive support for this prediction. We measure output conflict using geocoded data on riots and violence against civilians from the Armed Conflict Location and Event Dataset (ACLED; 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 1 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 nonfood 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 that cover 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 effect is much larger in areas where food crops are produced relative to areas where cash crops are produced.

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.[3] 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)

[3] See Gurr (2010 [1970]) and Horowitz (1985) for influential theories of political and ethnic grievance motives for conflict, respectively. We are careful to note that these economic and grievance theories are 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. However, they do find that economic motives are more consistent with the evidence than grievance-based accounts.

argue that the relationship reflects instead the state capacity mechanism. Seminal work by Miguel, Satyanath, and Sergenti (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 (Ciccone 2011; Miguel and Satyanath 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 (Hsiang, Burke, and Miguel 2013; Dell, Jones, and Olken 2014; Burke et al. 2015; Sarsons 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 (Collier and Hoeffler 2005; Koubi et al. 2014; Ross 2015). 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, Bazzi and Blattman (2014) find that higher prices reduce the duration of existing conflicts and have no effect on the onset of new conflicts. More recently, Bellemare (2015) and van Weezel (2016) find that higher food prices are linked to civil unrest at the country level.

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 (2018) 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 those of 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 findings and by establishing new ones. 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 in one direction in food-producing cells and in the opposite direction in food-consuming cells. This strategy also allows us to cleanly isolate the opportunity cost channel from the observationally similar state capacity channel. By identifying opposing effects of a price shock within a state-period, we provide clear evidence that the opportunity cost channel is an important mechanism through which economic shocks affect conflict, overcoming a long-standing problem in the literature.

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, Brückner and Ciccone (2010) and Bazzi and Blattman (2014) 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 to 2008 on the average cell-level probability of conflict battles in Africa was actually positive, comprising 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.[4] Moreover, our finding that food prices increase output conflict differentially in food-producing areas adds a new dimension to our understanding of

[4] Harari and La Ferrara (2018) and Bazzi and Blattman (2014), among many others, use different measures of violence as dependent variables either in 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 affect each of their four main measures of violence similarly (i.e., 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 are associated with the predation motive—perhaps as a tool for extortion—but not with the type of violence driven by the opportunity cost motive.

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 combine our results with leading forecasts of future grain prices to estimate the projected change in conflict from 2010 to 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 of 10% in factor conflict and 30% in output conflict. More than half of the overall change can be attributed to the effects of climate change alone.

We proceed in section II with our theoretical framework for the analysis and with a discussion of two illustrative case studies. Section III introduces the data and provides a background on global food price variation. In sections IV and V, we present our estimation strategy and results, respectively. In section VI, we discuss the magnitude of our results and conclude.

II. 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 begin with the case of factor conflict, where conflict is characterized as competition over land, as in Chassang and Padró i Miquel (2009). We then analyze the case of output conflict, characterized instead as competition over output, as in Dal Bó and Dal Bó (2011). In so doing, we highlight how the type of conflict under analysis can determine the predicted effect of food prices. We study the two types of conflict separately for ease of exposition. We allow for both types of conflict simultaneously in appendix A.5 (apps. A–C are available online).

We define producers as subnational polities that control rents from landownership. These groups solve a dynamic problem in which they can either (1) farm peacefully in the productive sector or (2) launch armed attacks to acquire territory through the technology of factor conflict.

Consumers are atomistic agents who decide between (1) providing wage labor in the productive sector and (2) providing wage labor to an armed group engaging in factor conflict. Later, we allow consumers to appropriate producer surplus directly through the technology of output conflict.

Our goal is to derive qualitative comparative statics in order to determine the effect of crop price movements on these decisions. Underpinning our analysis is an assumption 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. We examine the role of this assumption empirically in section V.E.

A. Environment

1. Producers

Consider two identical producer groups $g \in \{1, 2\}$ who each initially control one half of a territory of size $\bar{N}$ and employ L_{gt} units of labor at time t. Each group can either allocate all of this labor to farming or divert a fixed share $L^{V} \in (0, 1]$ from production to soldiering in an attempt to seize the other's land through the technology of factor conflict.[5] Group g's revenue in period t is generated as follows:

$$Y_{gt}(P_{jt}, N_{gt}, L_{gt}) = P_{jt} N_{gt}^{\alpha} (L_{gt}(1 - L_{gt}^{V}))^{1-\alpha}, \tag{1}$$

where P_{jt} is the price of crop j; N_{gt} is the area of land that group g controls in period t; $L_{gt}^{V} \in \{0, L^{V}\}$ represents the decision to attack; and $0 < \alpha < 1$.

An offensive advantage is obtained by launching the first attack, giving a group victory with probability $\pi > 1/2$. If both groups attack simultaneously, they each win with probability $1/2$. War is decisive; the victor controls the entire territory indefinitely.[6]

Groups seek to maximize the present discounted value of production net of total labor costs:

$$\sum_{t=t_0}^{\infty} \delta^{t-t_0} \left\{ P_{jt} N_{gt}^{\alpha} \left[L_{gt}(1 - L_{gt}^{V}) \right]^{1-\alpha} - w_{jt} L_{gt}(1 - L_{gt}^{V}) - w_t^{V} L_{gt} L_{gt}^{V} \right\}, \tag{2}$$

where w_{jt} is the wage rate per unit of farm labor; w_t^{V} is the wage rate per unit of soldiering labor; $\delta \in (0, 1)$ is a time discount factor; t_0 is the base period; and

$$N_{gt} = \begin{cases} \dfrac{\bar{N}}{2}, & \text{if conflict has never occurred,} \\ \bar{N}, & \text{if conflict has occurred and } g \text{ won,} \\ 0, & \text{if conflict has occurred and } g \text{ lost.} \end{cases} \tag{3}$$

This condition captures the idea that groups begin each period with $\bar{N}/2$ unless there is conflict in the previous period, in which case they control $\bar{N}$ thereafter if they defeat the other group and 0 otherwise.

[5] An alternative approach would allow producers to hire additional labor from other regions and not divert resources from production. While this is perhaps possible, existing evidence suggests that armed groups in Africa are substantially resource constrained as they expand their activity when given a windfall, e.g., from an increase in mining revenue, as in Berman et al. (2017). Rather than modeling these credit constraints, we stipulate that producers instead have to hire a fixed number of local consumers in each period to either farm or fight.

[6] Our model does not explicitly incorporate the role of retaliation (e.g., via alliances); however, we could approximate this by reducing the value of π. This would reduce the expected benefit of conflict. We thank a referee for pointing this out. We also make the further assumption that conflict requires a positive amount of labor, thus ruling out the special case where $L_{gt}^{V} = L^{V}$ and $L_{gt} = 0$.

Each group has an initial endowment of labor $L_{gt} = 1$. The choice facing each group in the initial period is either to divert a share L^{V} of labor to soldiering or instead to use all labor for farming. In subsequent periods, groups choose the total amount of labor L_{gt} optimally.

2. Crop Prices and Types

In each period, the world crop price P_{jt} is 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 shocks to international market conditions that are independent over time. Total potential income Y_t can therefore vary exogenously over periods, while always remaining positive. We assume that $\mu_j > 0$ and $0 \leq \phi < 1$, implying that shocks are not permanent.[7]

We consider price movements for three types of crops: $\mathbf{P}_t = [P_{ct}, P_{mt}, P_{ft}]$. The first element, P_{ct}, is the price of a *cash crop*, a crop that is produced in a given cell but consumed elsewhere. The second element, P_{mt}, is the price of a staple *import crop*, a crop that is consumed in a given cell but produced elsewhere. The third element, P_{ft}, is the price of a staple *food crop*, a crop that is both produced and consumed in a given cell.

Let $j \in \{c, f\}$ denote the domestically produced crops, and $x \in \{m, f\}$ denote the domestically consumed crop, where $x = m$ indicates that it is imported. A territory will either produce crop c and consume m or it will produce and consume crop f. Whether a territory grows c or f is exogenously determined by geographical characteristics such as soil suitability. We assume that the shock terms ϵ_{jt} are independent across crops j.

3. Consumers

Individuals supply labor and consume crop output. Each consumer i maximizes utility $U_{it}(x_{it})$, subject to a budget constraint $P_{xt} x_{it} = w_{it}$, where $U'_{it}(\cdot) > 0$, $U''_{it}(\cdot) < 0$, x_{it} is a quantity of the domestically consumed crop, and w_{it} is wage income. Consumers do not own land; they can supply farm labor for a wage rate w_{jt}, supply soldier labor for a wage rate w^{V}_{jt}, or directly appropriate output from producers. We assume that consumers can change locations between periods but not within periods: they make a locational decision and then chose to farm, fight, or steal.

4. Farm Wages

Farm wages in Africa adjust to international output prices incompletely and with a lag, in part as a result of the seasonality of agricultural production

[7] We examine the empirical case for this assumption in app. 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. 2016), suggesting that supply is elastic in the long run.

decisions (Ivanic and Martin 2014; Headey and Martin 2016). This empirical fact is captured by the idea that consumers cannot migrate within periods (the short run) but can migrate between periods. Thus, we assume that farm wages are increasing in the previous period's output price: $w_{jt} = w_{jt}(P_{jt-1})$ where $\partial \log w_{jt}(P_{jt-1})/\partial \log P_{jt-1} = \eta$ for all j and t and for $0 \le \eta \le \phi$.[8]

5. Soldiering Wages

Soldiering involves the risk of fatality or physical harm. Let λ_i represent individual i's probability of surviving a given battle without major harm, where λ_i is drawn according to a cumulative distribution function $G(\lambda_i)$. Armed groups will set the soldiering wage w_{jt}^{V} so that, for the marginal consumer,

$$v_{it}(\mathbf{P}_t, w_{it} \mid w_{it} = w_{jt}(P_{jt-1})) + \widehat{v_{it}} = \lambda_i\big(v_{it}(\mathbf{P}_t, w_{it} \mid w_{it} = w_{jt}^{\mathrm{V}}) + \widehat{v_{it}}\big), \quad (4)$$

where $v_{it}(\mathbf{P}_t, w_{it})$ represents the consumer's indirect utility function and $\widehat{v_{it}}$ is the present value of future consumption. The marginal consumer's λ^* is therefore given by the solution to $G(\lambda^*) = 1 - L^{\mathrm{V}}$, where L^{V} is the share of labor that must be diverted to soldiering if the producer decides to attempt to seize land. This characterizes the idea that those who exhibit higher values of λ_i have more to gain from fighting and will therefore fight even when L^{V} is low. Conversely, those with the least to gain will be the last to fight.

This feature implies that armed groups must provide a soldiering premium of $\omega = w_{jt}^{\mathrm{V}} - w_{jt}(P_{jt-1}) > 0$ in order to compensate for this risk and attract a supply of labor for factor conflict. Because of consumers' diminishing marginal utility, armed groups set a lower soldiering premium when real wages are low and a higher soldiering premium when real wages are high, all else equal. To see this, note that consumers will derive more utility from a given soldiering premium when their consumption levels fall. This increases the supply of labor to armed groups, which in turn lowers the equilibrium soldiering wage premium. We therefore denote this soldiering wage premium as a function of real wages: $\omega_{jt}(w_{jt}(P_{jt-1})P_{xt}^{-1})$, where $\omega_{jt}'(\cdot) > 0$.

[8] This lag is one of the reasons why the effect of a food price shock on poverty changes over time. The first-order effect is that real wages fall for net consumers of food in the short run because of rising consumer prices (Deaton 1989; Ivanic and Martin 2014). In the long run, producers can respond to higher prices by increasing agricultural supply, which raises the demand for labor and therefore rural wages and employment (although production decisions may not respond at all to sufficiently short-lived price shocks). In simulations, Ivanic and Martin (2014) estimate that the short-run effects are adverse in all nine of the African countries in their analysis, while the net effects (i.e., allowing for supply responses) are still adverse in six, implying that η is low. See Headey and Martin (2016) for a review of this literature.

B. Analysis: Factor Conflict and Crop Prices

We first consider the effect of price changes on factor conflict. In period t, each group faces a decision to farm peacefully or to attack unilaterally, represented by $L_{gt} \in \{0, L^{\mathrm{V}}\}$. If one side attacks, there is a decisive war between the two groups, after which the attacker, with probability $\pi > 1/2$, captures both groups' output at t and controls the entire territory $\bar{N}$ into the future. If both sides attack simultaneously, they each win with probability 1/2. If neither side attacks, each group farms $\bar{N}/2$ in every period thereafter.[9] The goal of our model is to determine how prices affect this decision.

The game proceeds as follows. (1) Two identical, fully informed groups begin with initial endowments $N_{gt} = \bar{N}/2$ and $L_{gt} = 1$; (2) $\mathbf{P}_t$ is revealed and observed by both groups; (3) if it is profitable for neither side to deviate unilaterally from peace, there is no war and each group continues to farm $\bar{N}/2$ indefinitely; (4) if not, there is a decisive war.[10]

1. Payoffs

Let $V_g(L_{gt}^{\mathrm{V}}, L_{-gt}^{\mathrm{V}})$ represent group g's payoff from choosing $L_{gt}^{\mathrm{V}} \in \{0, L^{\mathrm{V}}\}$ conditional on group $-g$ choosing $L_{-gt}^{\mathrm{V}} \in \{0, L^{\mathrm{V}}\}$. The payoffs are symmetrical and are represented as follows:

$$\begin{aligned} V_g(L^{\mathrm{V}}, L^{\mathrm{V}}) = {} & \frac{1}{2}\left[2P_{jt}\left(\frac{\bar{N}}{2}\right)^{\alpha}(1 - L^{\mathrm{V}})^{1-\alpha} + \delta V_t^{\mathrm{V}}(P_{jt}, w_{jt}(P_{jt-1}))\right] \\ & - w_{jt}(P_{jt-1})(1 - L^{\mathrm{V}}) - w_{jt}^{\mathrm{V}}(w_{jt}(P_{jt-1})P_{xt}^{-1})L^{\mathrm{V}}, \end{aligned} \tag{5}$$

$$\begin{aligned} V_g(0, L^{\mathrm{V}}) = {} & (1 - \pi)\left[2P_{jt}\left(\frac{\bar{N}}{2}\right)^{\alpha}(1 - L^{\mathrm{V}})^{1-\alpha} + \delta V_t^{\mathrm{V}}(P_{jt}, w_{jt}(P_{jt-1}))\right] \\ & - w_{jt}(P_{jt-1})(1 - L^{\mathrm{V}}) - w_{jt}^{\mathrm{V}}(w_{jt}(P_{jt-1})P_{xt}^{-1})L^{\mathrm{V}}, \end{aligned} \tag{6}$$

$$\begin{aligned} V_g(L^{\mathrm{V}}, 0) = {} & \pi\left[2P_{jt}\left(\frac{\bar{N}}{2}\right)^{\alpha}(1 - L^{\mathrm{V}})^{1-\alpha} + \delta V_t^{\mathrm{V}}(P_{jt}, w_{jt}(P_{jt-1}))\right] \\ & - w_{jt}(P_{jt-1})(1 - L^{\mathrm{V}}) - w_{jt}^{\mathrm{V}}(w_{jt}(P_{jt-1})P_{xt}^{-1})L^{\mathrm{V}}, \end{aligned} \tag{7}$$

$$V_g(0, 0) = P_{jt}\left(\frac{\bar{N}}{2}\right)^{\alpha} - w_{jt}(P_{jt-1}) + \delta V_t^{\mathrm{P}}(P_{jt}, w_{jt}(P_{jt-1})). \tag{8}$$

[9] Allowing for the possibility of future conflict does not substantively affect the model's conclusions. See app. A.2 for a discussion on this.

[10] We show in app. A.3 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 $\bar{N}/2$ avoids conflict. We therefore consider the case in which each group controls $\bar{N}/2$ rather than explicitly modeling this transfer decision.

The gains from fighting consist of both groups' production at period t less the aggregate opportunity cost of fighting, plus the continuation value of victory, $V_t^{\mathrm{V}}(\cdot)$. When both sides attack simultaneously, group g's gains are realized with probability 1/2. When group $-g$ strikes first, group g's gains are realized with probability $1-\pi$. When group g strikes first, its gains are observed with probability π. In all three cases, group g accrues labor costs from both farming and soldiering. If neither side attacks, then group g receives profits from farming $\bar{N}/2$ plus the continuation value of peace, $V_t^{\mathrm{P}}(\cdot)$.

2. Equilibrium

Attacking is always the best response to attacking, as $V_g(L^{\mathrm{V}}, L^{\mathrm{V}}) > V_g(0, L^{\mathrm{V}})$, $\forall\ P_{gt} \in (0, \infty)$. The equilibrium of this game will be determined by the relative sizes of $V_g(L^{\mathrm{V}}, 0)$ and $V_g(0, 0)$. If $V_g(L^{\mathrm{V}}, 0) > V_g(0, 0)$, then attacking is a dominant strategy for both groups. However, if $V_g(L^{\mathrm{V}}, 0) < V_g(0, 0)$, then it is not profitable for either group to deviate unilaterally from the initial peace.

We can express this condition for peace as

$$\begin{gathered} P_{jt}\left(\frac{\bar{N}}{2}\right)^{\alpha}\left[1 - 2\pi(1 - L^{\mathrm{V}})^{1-\alpha}\right] > \\ \delta\left(\pi V_t^{\mathrm{V}}(P_{jt}, w_{jt}(P_{jt-1})) - V_t^{\mathrm{P}}(P_{jt}, w_{jt}(P_{jt-1}))\right) - L^{\mathrm{V}}\omega_{jt}(w_{jt}(P_{jt-1})P_{xt}^{-1}). \end{gathered} \tag{9}$$

The left-hand side is the net opportunity cost of conflict due to forgone output in time t.[11] The first term on the right-hand side is the present value of the gains from conflict due to future profits. The second term on the right-hand side is the additional labor cost of conflict. Note that the likelihood of a peaceful equilibrium is increasing in L^{V}, the share of labor that must be diverted from production to conflict, and decreasing in π, the offensive advantage to the first attacker.

In order to determine how price shocks will affect this decision, we must express $V_t^{\mathrm{V}}(\cdot)$ and $V_t^{\mathrm{P}}(\cdot)$ in terms of P_{jt}. As victory confers total control over all of $\bar{N}$, the value of $V_t^{\mathrm{V}}(\cdot)$ will be the solution to

$$\max \mathbb{E}\left[\sum_{t'=t}^{\infty}\delta^{t'-t}(P_{jt'+1}\bar{N}^{\alpha}L_{gt'+1}^{1-\alpha} - w_{jt'+1}(P_{jt'})L_{gt'+1})\right],$$

the expected value of farming all of $\bar{N}$ in the long run when groups can hire the optimal amount of L_{gt} in between future seasons at a wage rate $w_{jt}(\cdot)$. Solving for this yields the following observation:

[11] This is the net opportunity cost because when group g attacks it gives up $P_{jt}(\bar{N}/2)^{\alpha}$ with probability 1 and gains $2P_{jt}(\bar{N}/2)^{\alpha}(1 - L^{\mathrm{V}})^{1-\alpha}$ with probability π.

$$\pi V_t^{\mathrm{V}}(\cdot) - V_t^{\mathrm{P}}(\cdot)$$
$$= \left(\pi - \frac{1}{2}\right) \mathbb{E}\left[\sum_{t'=t}^{\infty} \delta^{t'-t} \left\{ \frac{P_{jt'+1}(P_{jt'})^{1/\alpha}}{w_{jt'+1}(P_{jt'})^{(1/\alpha)/\alpha}} \bar{N}\left[(1-\alpha)^{(1/\alpha)/\alpha} - (1-\alpha)^{1/\alpha}\right] \right\}\right] > 0, \tag{10}$$

as $V_t^{\mathrm{P}}(\cdot) = (1/2)V_t^{\mathrm{V}}(\cdot)$ and $\pi > 1/2$.

Under three conditions, there exists a unique fixed point at which the costs and benefits of conflict are equated. First, the term on the left-hand side of (9) is increasing linearly in P_{jt}. This is true if $1 - 2\pi(1 - L^{\mathrm{V}})^{1-\alpha} > 0$. Second, the first term on the right-hand side is an increasing concave function of P_{jt}. This is true if its elasticity with respect to P_{jt} is between 0 and 1, or $(1/\alpha)\cdot[\phi/(1-\delta\phi)] - [(1-\alpha)/\alpha]\cdot[\eta/(1-\delta\phi)] < 1$, from (10). Third, when P_{jt} is close to 0, the gains from conflict due to future profits remain sufficiently high to offset the total costs accrued at t, or $\forall\ P_{jt} \in (0, \varepsilon)$, where ε is an arbitrarily small value of P_{jt},

$$P_{jt}\left(\frac{\bar{N}}{2}\right)^{\alpha}\left[1 - 2\pi(1 - L^{\mathrm{V}})^{1-\alpha}\right] < \delta(\pi V_t^{\mathrm{V}}(\cdot) - V_t^{\mathrm{P}}(\cdot)) - L^{\mathrm{V}}\omega_{jt}\left(w_{jt}(P_{jt-1})P_{xt}^{-1}\right). \tag{11}$$

It follows that groups are willing to maintain peace for values of P_{jt} above some threshold $\tilde{P}_{jt}$ and that they will unilaterally deviate from peace for values of P_{jt} below $\tilde{P}_{jt}$. When we substitute (10) into (9), this threshold price is implicitly defined by

$$\tilde{P}_{jt}\left(\frac{\bar{N}}{2}\right)^{\alpha}\left[1 - 2\pi(1 - L^{\mathrm{V}})^{1-\alpha}\right]$$
$$= \delta\left(\pi - \frac{1}{2}\right)\mathbb{E}\left[\sum_{t'=t}^{\infty}\delta^{t'-t}\left\{\frac{P_{jt'+1}(\tilde{P}_{jt'})^{1/\alpha}}{w_{jt'+1}(\tilde{P}_{jt'})^{(1-\alpha)/\alpha}}\bar{N}\left[(1-\alpha)^{(1-\alpha)/\alpha} - (1-\alpha)^{1/\alpha}\right]\right\}\right]$$
$$- L^{\mathrm{V}}\omega_{jt}\left(w_{jt}(P_{jt-1})P_{xt}^{-1}\right). \tag{12}$$

This characterizes the threshold price at which the opportunity cost of conflict (on the left-hand side) is equal to the direct gains from conflict net of additional labor costs (on the right).

PROPOSITION 1. There exists a price $\tilde{P}_{jt} > 0$ such that groups will unilaterally deviate from peace for realizations of $P_{jt} < \tilde{P}_{jt}$.

Kennan (2001) demonstrates that the properties outlined above ensure a unique fixed point. The conditions and their implications are intuitive. The first condition is that there indeed exists a positive net opportunity cost of conflict in terms of forgone production: $1 - 2\pi(1 - L^{\mathrm{V}})^{1-\alpha} > 0$. This condition implies that the opportunity cost is a positive linear function of P_{jt}, $\forall\ P_{jt} \in (0, \infty)$. The second condition is that the persistence of a price shock over time is sufficiently low, which can be simplified to $\phi < [\alpha + \eta(1 - \alpha)]/(1 + \alpha\delta)$. This implies that the gains from conflict due to future profits are a strictly increasing and strictly concave function of P_{jt}, $\forall\ P_{jt} \in (0, \infty)$. The final condition is that these gains from conflict exceed the opportunity cost when P_{jt} is arbitrarily low (condition [11]). This ensures that the concave function (representing the gains from conflict) intersects the linear function (representing the opportunity cost of conflict) at a unique positive fixed point.

This latter condition is plausible because of the stochastic price process defined above. As P_{jt} approaches zero, the left-hand side of (12) approaches zero. However, the right-hand side of (12) need not converge with the left, as $P_{jt+1} = e^{u_j + \phi \log P_{jt} + \epsilon_{jt}}$. In other words, if P_{jt} is close to zero, the present value of future profits will exceed the opportunity cost of conflict at t, provided that either u_j is sufficiently high or ϕ is sufficiently low.[12]

The intuition behind proposition 1 is based on the transitory nature of price shocks: starting at the point where $P_{jt} = \tilde{P}_{jt}$, a fall in P_{jt} will have a greater negative effect on the opportunity cost of fighting (lost profits from farming in time t) relative to the present value of victory (permanent control of land), provided that ϕ, the persistence of price shocks over time, is sufficiently low. This feature generates our first prediction: attacking is more likely to be a dominant strategy for both groups at lower realizations of P_{jt}, while a peaceful equilibrium is more likely to be maintained at higher realizations of P_{jt}.

3. Consumer Prices

Equation (12) also implies that a shock to the soldiering wage premium ω_{jt} will affect the value of the threshold price $\tilde{P}_{jt}$ by shifting the right-hand-side function. The condition in equation (4) states that groups set w_{jt}^{V} such that the certainty equivalent for the marginal consumer is w_{jt}. Concave utility implies that if the real farming wage falls (exogenously), soldiering becomes more attractive to consumers because of this wage premium. This increases the supply of labor to armed groups and lowers the equilibrium soldiering wage premium in the process.

It follows that a rise in P_{xt}—the price of a crop consumed within a cell—reduces real wages $w_{jt}(P_{jt-1})P_{xt}^{-1}$ independently of P_{jt}, which in turn lowers

[12] For example, evaluated for any $P_{jt} \in (0, \varepsilon)$, the concave function on the right-hand side of (12) increases exponentially as u_j increases, while the left-hand side remains close to zero. This implies that condition (11) is satisfied above a certain value of u_j. Intuitively, permanent control of land becomes more valuable relative to output at t. Similarly, if ϕ is zero, then the right-hand side of (12) is a horizontal line, as P_{jt} contains no information on future profits. If the first term is greater than $L^{V}\omega_{jt}(\cdot)$, then condition (11) is satisfied and there is a positive and unique fixed point.

the equilibrium soldiering wage premium. More formally, as $w_{jt}^{\mathrm{Y}}(\cdot) > w_{jt}(\cdot)$ and $U_{it}''(\cdot) < 0$, then

$$\frac{\partial v_{it}(\mathbf{P}_t, w_{it}|w_{it} = w_t)}{\partial P_{xt}} < \frac{\partial v_{it}(\mathbf{P}_t, w_{it}|w_{it} = w_t^{\mathrm{Y}})}{\partial P_{xt}}. \tag{13}$$

PROPOSITION 2. An increase in consumer food prices P_{xt} reduces the wage premium $\omega_{jt}(\cdot)$ and increases $\tilde{P}_{jt}$, the threshold crop price below which groups unilaterally deviate from peace.

The proof comes from equations (4) and (13), which together imply that higher consumer food prices P_{xt} will increase the supply of labor to armed groups—reducing the soldiering wage premium—and equation (12), which implies in turn that this will increase the range of domestic crop prices over which attacking is a dominant strategy for both groups. Intuitively, rising food prices induce some consumers to switch from low-wage agriculture to higher-wage (but riskier) soldiering through an income effect, all else equal.[13] This lowers the relative cost of factor conflict for potential armed groups, as soldiers are cheaper to hire.[14]

C. Output Conflict and Crop Prices

In this section, we characterize conflict as a competition over output rather than land. We do so by allowing consumers to directly appropriate producers' surplus through the technology of output conflict as an alternative to providing wage labor. We denote by L^{Q} the share of labor in this appropriation sector and by $Q(L^{\mathrm{Q}})$ the fraction of total output that is redistributed from the productive sector to the appropriation sector, where the function $Q(L^{\mathrm{Q}})$ is positive, continuous, and strictly concave as a result of congestion effects, as in Dal Bó and Dal Bó (2011).

We first characterize equilibrium output conflict. In the absence of factor conflict, the total value of appropriated output in each cell is $Q(L^{\mathrm{Q}})[P_{jt}(\bar{N}/2)^{\alpha}(1 - L^{\mathrm{Q}})^{1-\alpha} + P_{xt}M_{xt}]$, where $M_{xt} \in \{0, \bar{M}_t\}$ represents a

[13] This analysis implies that rising domestically produced crop prices P_{jt} will reduce factor conflict as farming becomes relatively profitable for groups (proposition 1), while rising domestically consumed food prices P_{xt} will increase factor conflict as the soldiering wage premium becomes more valuable to consumers (proposition 2). Clearly, we cannot speak to the overall effect of price changes where $j = x = f$. However, we do separate these effects in the empirical section below.

[14] We do not consider second-order effects of prices on ω_t due to future wages, whereby, from eq. (4), an increase in P_{jt} will increase $\widehat{v}_{it}$, which will in turn increase ω_{jt} as groups must further compensate soldiers because of λ. Allowing for these effects further supports the predictions established in both propositions: rising P_{jt} implies rising ω_{jt}, which reduces the incentive to attack. This yields the prediction that conflict is less profitable at higher realizations of P_{jt}, which is consistent with proposition 1. Conversely, rising P_{xt} implies lowering ω_{jt}, which increases the incentive to attack. This yields the prediction that conflict is more profitable at higher realizations of P_{xt}, which is consistent with proposition 2.

steady state of imported food stocks such that $M_{mt} = \bar{M}_t$ and $M_{ft} = 0$. Again drawing on Dal Bó and Dal Bó (2011), a consumer's decision to appropriate is determined by the following condition:

$$\frac{Q(L^Q)}{P_{xt}L^Q}\left[P_{jt}\left(\frac{\bar{N}}{2}\right)^{\alpha}(1 - L^Q)^{1-\alpha} + P_{xt}M_{xt}\right] = (1 - Q(L^Q))w_{jt}(P_{jt-1})P_{xt}^{-1}, \quad (14)$$

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 the right-hand side is the payoff from one unit of productive work net of appropriation. Both sides are adjusted for purchasing power. A consumer will appropriate as long as it is profitable to do so. We show in appendix A.4 that there is a unique equilibrium level of appropriation L^Q determined by the equality in (14).

Our goal is to determine how shocks to crop prices will affect this equilibrium. Denoting by $\mathbb{A}_{jt}$ the left-hand side of (14) and by $\mathbb{W}_{jt}$ the right-hand side, the equilibrium level of appropriation will increase if a price shock raises the marginal consumer's payoff from appropriation more than it raises the payoff from labor, or $\mathbb{A}'_{jt} > \mathbb{W}'_{jt}$.[15]

1. Food Crops ($j = x = f$)

We begin by examining a change to P_{ft} where $j = x = f$. Note from the left-hand side of (14) that $\mathbb{A}'_{ft} = 0$, as the price terms cancel out. It is clear from the right-hand side of (14) that higher food crop prices reduce consumers' real wages: $\mathbb{W}'_{ft} < 0$. Combining these observations, a food price shock will increase output conflict until both sides of (14) are equated.

2. Cash Crops ($j = c$; $x = m$)

We now examine a change to P_{ct} where $j = c$ and $x = m$. A rise in P_{ct} increases the value of appropriable output, as $\mathbb{A}'_{ct} > 0$. There is no change to consumers' real wage: $\mathbb{W}'_{ct} = 0$. Thus, a cash crop shock will increase output conflict.[16]

[15] We show in app. A.5 that the presence of factor conflict does not affect the qualitative nature of the comparative statics presented below. For now, it is worth noting from eq. (4) that factor conflict groups set w_{jt}^V so as to equate the expected utilities of farm and soldiering labor for the marginal consumer. We can therefore interpret $\mathbb{W}_{jt}$ as the payoff from one unit of labor—either farming or soldiering—for the marginal consumer.

[16] We can allow for the effect of prices through $w_{jt}(P_{jt-1})$ by considering the lagged impact of price shocks. When $j = x = f$, the lagged effect is ambiguous. This is because w_{ft+1} increases though η (raising the numerator in $\mathbb{W}_{ft+1}$) while P_{ft+1} increases through ϕ (raising the denominator). Similarly, when $j = c$, the lagged effect is also ambiguous. This is because P_{ct+1} increases through ϕ (raising $\mathbb{A}_{ct+1}$), while w_{ct+1} increases through η (raising $\mathbb{W}_{ct+1}$).

PROPOSITION 3. $\mathbb{A}'_{jt} > \mathbb{W}'_{jt}$. An increase in domestically produced crop prices P_{jt} will raise the equilibrium level of output conflict.

When $j = x = f$, this prediction is due to a change in the opportunity cost of output conflict for consumers. A positive shock to P_{ft} does not affect the real value of appropriable output; rather, it reduces the value of real wages in the productive sector.

When $j = c$ and $x = m$, this prediction is due to a change in the value of appropriable output. A positive shock to P_{ct} does not affect real wages in the productive sector and therefore has no impact on the opportunity cost of output conflict for consumers.

Owing to concave utility, the difference between these mechanisms implies that a given shock to the opportunity cost of output conflict (caused by a change in P_{ft} when $j = x = f$) will have a larger effect on output conflict than an equivalent shock to the value of appropriable surplus (caused by a change in P_{ct} when $j = c$ and $x = m$). This is because the lost utility from the $\mathbb{W}'_{ft}$ shock will be larger than the utility to be gained from an equivalent $\mathbb{A}'_{lt}$ shock, thus rendering output conflict more profitable.

3. Import Crops ($j = c$; $x = m$)

Finally, we examine a change to P_{mt}, the price of a crop that is consumed in a given cell but produced elsewhere. From the right-hand side of (14), $\mathbb{W}'_{mt} < 0$: higher import crop prices reduce real wages. From the left-hand side, a shock to P_{mt} also reduces the real value of appropriable cash crop output (the first term in parentheses) but not the value of appropriable import crops (the second term), which remains constant in real terms. Thus, when $j = c$ and $x = m$, a shock to P_{mt} raises the value of output conflict by lowering its opportunity cost.

PROPOSITION 4. $\mathbb{A}'_{mt} > \mathbb{W}'_{mt}$. An increase in imported food prices P_{mt} raises the equilibrium level of output conflict when $j = c$ and $x = m$.

A change to P_{mt} reduces real wages in the productive sector without altering the real value of import crops. This will induce marginal consumers to appropriate until the terms in (14) are equilibrated.

D. Combining Factor and Output Conflict

In appendix A.5, we allow for producers and consumers to make their optimal decisions in the presence of both factor conflict and output conflict. We model factor conflict as a state variable and show that its presence does not qualitatively alter the output conflict predictions in propositions 3 and 4. In turn, the exercise allows us to refine the conditions necessary for the factor conflict predictions in propositions 1 and 2 to hold. We show that higher domestic crop prices will still lead groups to farm rather than fight as long as the second-order (net) impact of prices on output conflict does not offset the opportunity cost of factor conflict in terms of lost production. Similarly, higher import crop prices will still lead to factor conflict as long as the wage premium reduction is not offset by the second-order effect (via output conflict) on the expected benefit of launching a factor conflict attack.[17]

E. *Summary and Discussion*

1. Summary

The following statements summarize the main predictions that we investigate empirically. "Domestically produced crops" are crops produced in a subnational cell.

1. Higher domestically produced crop prices P_{jt} reduce factor conflict, as groups choose to farm rather than attack the neighboring territory.
2. Higher consumer crop prices P_{xt} increase factor conflict, as consumers turn to armed groups for a higher wage.
3. Higher domestically produced crop prices P_{jt} increase output conflict, as consumers respond to the increasing value of output relative to real wages.
4. Higher consumer crop prices P_{xt} increase output conflict, as consumers respond to the increasing value of output relative to real wages.

2. Discussion

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 (2002–5) 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 after 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 1,370 lives were lost (Sundberg and Melander 2013).

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

[17] We also show, in app. A.6, that were we to allow producers to endogenously determine agricultural wages, there would not exist a wage that profitably avoids output conflict.

ethnoreligious tensions and more competition for land (Woods 2003; *Economic and Political Weekly* 2004; Wong 2005). Woods (2003, 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 −4.581% and −2.245%[18] Amid the larger-scale contest for central political control, examples of village-level "microconflicts" 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.[19] 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.[20] This was one of 63 elections in sub-Saharan Africa from 1990 to 2012 that are deemed to have exhibited irregularities by the African Elections Database.[21] However, it is one of only a handful that escalated into a full-blown civil war, which ultimately left more than 3,000 civilians dead.[22] It concluded with the Battle

[18] World Bank (https://data.worldbank.org/indicator/NY.GDP.PCAP.KD.ZG?cid=GPD_31&locations=CI).

[19] See, e.g., "Chocolate War Erupts in Ivory Coast," *Guardian*, May 13, 2004 (https://www.theguardian.com/world/2004/may/14/rorycarroll); "Land Quarrels Unsettle Ivory Coast's Cocoa Belt," *New York Times*, May 26, 2004 (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).

[20] "Ivory Coast: Death Squads on the Rise as Civil War Looms," *Guardian*, December 22, 2010, https://www.theguardian.com/world/2010/dec/22/ivory-coast-death-squads.

[21] For more information on this data set, see http://africanelections.tripod.com/about.html.

[22] This figure comes from Human Rights Watch, October 5, 2011, https://www.hrw.org/report/2011/10/05/they-killed-them-it-was-nothing/need-justice-cote-divoires-post-election-crimes.

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 conditions a decade earlier, prices for staple food crops—among the country's main imports—were also approaching record peaks. Our model (proposition 2) indicates that the poverty caused by these staple food price shocks incentivized some net consumers to join the armed conflict. In that light, it makes sense that only three out of 22 battles (13.6%) in the second civil war took place outside of urban areas, as compared to 19 out 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.[23]

Finally, it was widely reported that Liberian mercenaries fought in large numbers for Gbagbo, and perhaps even for Ouattara.[24] In a survey of former Liberian Civil War combatants conducted at the time of the Ivorian crisis, Blattman and Annan (2016, 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 also that the cross-price elasticity of labor supply between peaceful and illicit sectors more generally is substantial, as potential fighters are responsive to small changes in relative wages. This is an important assumption of our model.

Another important assumption in our model is that consumers have little access to conventional financial smoothing mechanisms that would obviate the need to engage in risky coping strategies in the wake of price shocks. The evidence suggests that this assumption is plausible. First, Ivanic, Martin, and Zaman (2012) estimate that the 2010–11 food price shock pulled 68 million net consumers in less developed countries below the $1.25-per-day extreme-poverty line, while also lifting 24 million producers above it.[25] Applying the same ratio of producer and consumer effects

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

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

[25] Dollars are purchasing power parity adjusted.

to the overall effects reported in Ivanic and Martin (2008), we estimate that the 2005–7 price spike pulled an estimated 162 million consumers below the extreme-poverty line.[26] These findings 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. The idea that poor households must engage in risky or costly coping behaviors in the face of such shocks is in keeping with evidence from a broad empirical literature (e.g., Oster 2004; Miguel 2005; de Janvry et al. 2006; Dupas and Robinson 2012).

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 15 countries, eight of which were African.[27] 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).[28] Examples of both can be found in Côte d'Ivoire, where, in 2008, then-President Gbagbo canceled custom duties after two days of violent protests in Abidjan;[29] and, during the 2011 shock, a UN Refugee Agency warehouse was looted in the agricultural market town of Guiglo (Raleigh et al. 2010).[30]

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 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 in the Mudug region. These are among many examples documented in ACLED (Raleigh et al. 2010), described in more detail below.

[26] This is derived from a nine-country sample, in which Ivanic and Martin 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.

[27] "Food Price Rise Sparks Protests," *Reuters*, May 15, 2008, http://www.reuters.com/article/us-food-prices-protests-idUSL1579452720080515.

[28] 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.

[29] "Riots Prompt Ivory Coast Tax Cuts," *BBC News*, April 2, 2008, http://news.bbc.co.uk/1/hi/world/africa/7325733.stm.

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

III. Data and Measurement

A. *Structure*

We construct a panel grid data set to form the basis of our main empirical analysis, consisting of 10,229 arbitrarily drawn 0.5×0.5–decimal degree cells (around 55 km $\times$ 55 km at the equator) covering the continent of Africa. The unit of analysis is the cell-year. The cell resolution is presented graphically in figure A1 (figs. A1–A7 are available online).

B. *Conflict*

1. 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 output.[31] The UCDP GED project is particularly suitable. It represents a spatially disaggregated edition of the well-known UCDP country-level conflict data set used frequently in the literature. It records events involving "the use of armed force by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death" (Sundberg and Melander 2013, 524). Moreover, it includes only dyads that have crossed a 25-death threshold in a single year of the 1989–2010 series.[32] The data are recorded from a combination of sources, including local and national media, agencies, NGOs (nongovernmental organizations), 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 1 if any conflict event took place and 0 otherwise. This reduces the potential for measurement error to bias results and is in line with the literature (Miguel, Satyanath, and Sergenti 2004; Bazzi and Blattman 2014; Nunn and Qian 2014; Berman et al. 2017).[33]

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

[32] For example, battles between the Uganda National Rescue Front 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.

[33] 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, September 21, 2007; "Scores Feared Dead as Nigerian Villagers Battle over Farmland," AFP (Agence France Presse), April 25, 2005; "Tension Runs High in West Ivory Coast Cocoa Belt. [20 killed.]," Reuters, November 14, 2002; "Five Killed as Tribes Battle over Land in Kenya's Rift Valley Region," AFP, February 13, 2006; "Tribes in Chad Feud over Land around Well, 50 Dead," Reuters, November 23, 2000.

Summary statistics for this measure of conflict incidence are presented in the top panel of table 1. The unconditional probability of observing a factor conflict event in a cell-year is 2.7%. The row immediately beneath displays the corresponding onset statistics, defined as $\mathbb{I}(\text{Conflict}_{it} = 1 \mid \text{Conflict}_{it-1} = 0)$, where i is a cell. Conditional on peace at $t - 1$, conflicts occur with probability of 1.4%. Beneath this again are offset statistics, defined as $\mathbb{I}(\text{Conflict}_{it+1} = 0 \mid \text{Conflict}_{it} = 1)$. 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%. In the main analysis, we model onset and offset in addition to incidence.[34]

2. Main Output Conflict Measure: ACLED Output Conflict

Following our theory, the output conflict measure must capture violence over the appropriation of surplus. These events are likely to be more transitory and less organized than large-scale factor conflict battles over the permanent control of territory. For this, the 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 the 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. Table 2 shows that the unconditional output conflict probability is 5%.[35]

[34] In robustness tests, we also use an alternative measure of factor conflict from ACLED. It records conflicts after which (nonstate) 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 that is likely to be a small subset: the unconditional probability of observing this event is 0.4%.

[35] ACLED data observations are accompanied by a brief note on the nature of each event. The output conflict events contain 3,438 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; 1,302 mentions of "raid-" (0.15); 1,083 mentions of "loot-" (0.12); 1,173 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).

TABLE 1
Summary Statistics: 1989–2013

Variable	Mean	Standard Deviation	Minimum	Maximum	*N*
	Conflict Variables				
UCDP, factor conflict:					
Incidence	.027	.162	0	1	225,038
Onset	.014	.119	0	1	222,159
Offset	.535	.499	0	1	6,083
ACLED, output conflict:					
Incidence	.05	.219	0	1	173,893
Onset	.028	.166	0	1	169,953
Offset	.452	.498	0	1	8,762
Afrobarometer survey, output conflict:					
Theft in past year	.313	.464	0	1	67,500
Violence in past year	.131	.337	0	1	67,533
	Selected Cell Variables				
Cropland cells	.633	.482	0	1	255,725
Cropland area %	.072	.138	0	1	255,725
Population	74,092	236,970	0	11,620,281	255,725
Urban population	21,269	187,815	0	11,045,346	255,725
Urban area %	.009	.039	0	.87	255,575
Distance to city with population ≥500k (km)	519	299	1	1,441	255,725
Luminosity, 1992	.24	.427	0	1	255,725
Luminosity, 2010	.396	.489	0	1	255,725

Note.—See sec. III for a description of these variables and their sources.

3. Micro-Level Output Conflict from Afrobarometer

We turn to the Afrobarometer survey series for micro-level measures of interpersonal output violence.[36] 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 1, we see that more than 31% of respondents report having experienced theft in the past year, while 13% have been victims of violence.[37] In validation tests (discussed in app. 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 data set in more detail in section V.C.

The top 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

[36] Afrobarometer Data, merged country data sets, round 1 (1999–2001), round 2 (2002–3), round 3 (2005–6), and round 4 (2008–9), available at http://www.afrobarometer.org.

[37] 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?”

TABLE 2
UCDP Factor Conflict, Producer Prices, and Consumer Prices

	Incidence 1(Conflict > 0)			Onset 1(Conflict Begins)			Offset 1(Conflict Ends)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Regression Estimates								
PPI	−.0042	−.0046	−.0043	−.0024	−.0029	−.0027	.0443	.0494	.0385
Conley SE	.001	.001	.001	.001	.001	.001	.018	.020	.017
p-value	.001	.000	.000	.002	.004	.001	.015	.014	.022
Two-way SE	.002	.001	.001	.001	.001	.001	.022	.023	.020
p-value	.007	.001	.002	.020	.006	.012	.044	.029	.060
CPI		.0023	.0064		.0015	.0054		−.0881	−.1066
Conley SE		.002	.005		.001	.003		.024	.085
p-value		.134	.218		.143	.071		.000	.209
Two-way SE		.001	.006		.001	.004		.026	.092
p-value		.116	.319		.161	.138		.001	.248
	Other Results and Specifications								
PPI impact (%)	−15.4	−17.2	−16.1	−16.3	−20.0	−18.7	8.3	9.2	7.2
CPI impact (%)		8.6	23.7		10.2	37.7		−16.5	−19.9
Wald test: PPI = CPI:									
Conley *p*-value		.000	.040		.002	.009		.000	.103
Two-way *p*-value		.000	.097		.002	.035		.001	.135
Country × year FE	Yes	No	No	Yes	No	No	Yes	No	No
Year FE	No	No	Yes	No	No	Yes	No	No	Yes
Country × time trend	NA	Yes	Yes	NA	Yes	Yes	NA	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225,016	204,820	204,820	222,132	202,297	202,297	5,108	4,631	4,631

Note.—The dependent variables are UCDP factor conflict incidence, onset, and offset dummies. The PPI and CPI are measured in terms of average temporal standard deviations. Reported effects are the sum of price coefficients at t, $t-1$ and $t-2$. Conley SE allow for serial and spatial correlation within a radius of 500 km. Two-way SE allow for serial correlation within cells and spatial correlation across cells within countries. PPI (CPI) impact indicates the effect of a 1 standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms. FE = fixed effects; NA = not applicable.

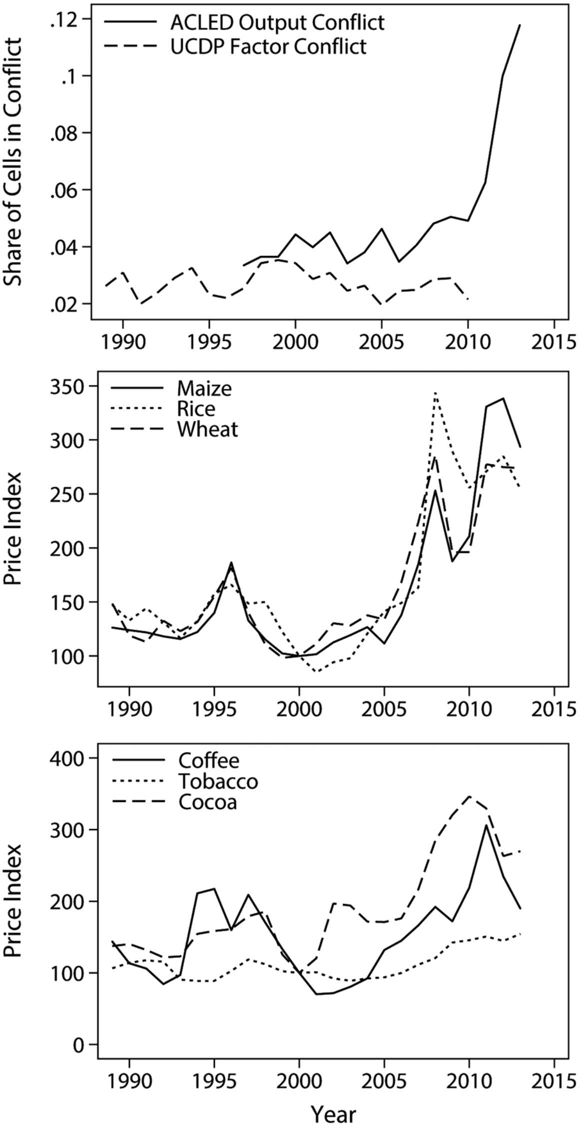

FIG. 2.—Conflict and price variables, 1989–2013. Conflict in the top panel is measured as the share of total cells in which at least one battle occurred each year. Price data are taken from IMF (International Monetary Fund) and World Bank sources (year 2000 = 100). See table A1.

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.

C. 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 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 bottom panels of figure 2 present sets of global crop price series covering 1989–2013, our period of analysis. The prices are taken from the IMF (International Monetary Fund) *International Finance Statistics* series and the World Bank *Global Economic Monitor* (described in more detail in app. B.1). The middle 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 bottom panel, we present a selection of three nonstaples ("cash crops"): 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 2008–9 and 2010–11. For instance, the surge in wheat prices is attributed to weather shocks in supplier countries such as Australia and China, while the concurrent maize price shock is jointly explained by rising demand for ethanol biofuels and high-fructose corn syrup and the effect of La Niña 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 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 appendix 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, Martin, and Zaman (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.

1. Producer Price Index (PPI)

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 data set of croplands by combining two different satellite-based data sets with detailed agricultural inventory data to train a land-cover classification data set. The method produces spatial detail at the 5-minute level (around 10 km at the equator), which we aggregate to our 0.5°-cell level. Table 1 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 PPI 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 l and year t the price index is given by[38]

$$\mathrm{PPI}_{ilt} = \sum_{j=1}^{n} \Bigg(P_{jt} \times \underbrace{N_{jil}}_{\text{crop share of land}} \Bigg), \tag{15}$$

where crops $j \ldots n$ are contained in a set of 11 major traded crops that feature in the M3-Cropland data set and for which international prices exist.

[38] Note that the subscript notation that we use hereafter in sec. III does not align perfectly with the subscript notation used in our theoretical model. For example, i now refers to a cell and j refers to crops in our data set.

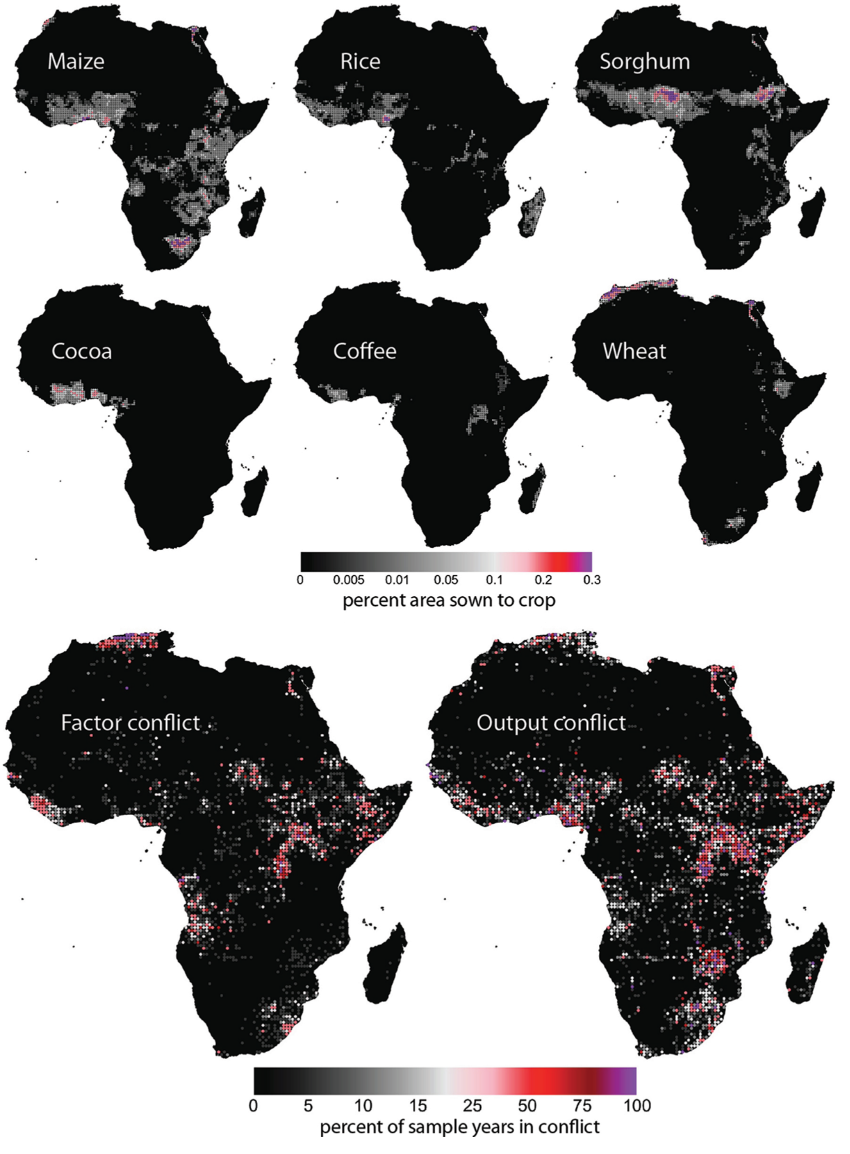

FIG. 3.—Geographic distribution of crops (year 2000) and total number of conflicts over the study period for the two conflict types.

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.[39] In addition to this aggregated index, we also

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

compute disaggregated variants: $\mathrm{PPI}_{ilt}^{\mathrm{food}}$ is an index of prices for food crops (those that constitute more than 1% of calorie consumption in the entire sample), and $\mathrm{PPI}_{ilt}^{\mathrm{cash}}$ is an index of prices for cash crops (the rest). The index varies over time only because of plausibly exogenous international price changes; all other components are fixed.

2. Consumer Price Index (CPI)

The CPI we construct is similar in structure to the PPI, but 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 is corrected for quantities fed to livestock and used as 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. These are similar to the crop shares N_{jil} above, except 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 CPI in cell i, country l and year t is given by

$$\mathrm{CPI}_{lt} = \sum_{j=1}^{n} \left(P_{jt} \times \underbrace{\xi_{jl}}_{\text{crop share of calories}} \right), \tag{16}$$

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 palm oil, which are used to process other foods. Again, temporal variation comes only from the price component.

D. Other Data

In table 1, "urban area %" is share of each cell area that is classified as urban by the SEDAC (Socioeconomic Data and Applications Center) project at Columbia University. The same source provides data on cell-level population (which we extrapolate from 5-year intervals to form a cell-year estimate) and distance to city (measured in kilometers).[40] "Luminosity" is

[40] SEDAC data sets are downloadable at http://sedac.ciesin.columbia.edu/data/sets/browse.

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 Defense Meteorological Satellite Program's Operational Linescan System, which reports images of the earth at night captured from 20:30 to 22:00 local time.[41]

IV. Estimation Framework

A. *Factor Conflict*

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

$$\begin{aligned} \text{Factor conflict}_{ilt} &= \alpha_i + \sum_{k=0}^{2}\beta^{\mathrm{p}}_{t-k}\mathrm{PPI}_{ilt-k} + \gamma_{lt} + \epsilon_{ilt}, \\ \text{Factor conflict}_{ilt} &= \alpha_i + \sum_{k=0}^{2}\beta^{\mathrm{p}}_{t-k}\mathrm{PPI}_{ilt-k} + \sum_{k=0}^{2}\beta^{\mathrm{m}}_{t-k}\mathrm{CPI}_{lt-k} + \gamma_l \times t + \epsilon_{ilt}, \end{aligned} \tag{17}$$

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_{lt} is country $\times$ year fixed effects (CYFEs); $\gamma_l \times t$ is a country-specific time trend; and ϵ_{ilt} 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 500 km, 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.[42] We sum price effects over three years to account for delayed effects of past shocks or potentially for displacement effects where shocks hasten conflict that would have happened in any case. We estimate the specification with both a linear probability model (LPM) and conditional logit, preferring LPM for the main analysis.

In line with propositions 1 and 2, 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.

[41] https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html. See Michalopoulos and Papaioannou (2013) for a discussion on the particular suitability of nighttime lights as measure for economic development in Africa.

[42] We show in the appendix (table A4) that our main results are robust to setting the Conley standard error distance cutoff from 100 to 1,000 km (in intervals of 100 km).

In the first specification, β^{p} is estimated from 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.[43] In the second specification, we include the CPI and substitute the country-year trend for CYFEs. 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 CPI and PPI is not correlated with unobserved factors that also affect conflict. 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). Nevertheless, we also present results from specifications that include year fixed effects. In the appendix (table A2; tables A1–A30 are available online), we additionally include cell-level controls for an oil price index, a mineral price index, and various weather controls.

B. *Output Conflict*

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

$$\begin{aligned}
\text{Output conflict}_{ilt} &= \alpha_i + \sum_{k=0}^{2}\theta^{\mathrm{p}}_{t-k}\mathrm{PPI}_{ilt-k} + \gamma_{lt} + e_{ilt},\\
\text{Output conflict}_{ilt} &= \alpha_i + \sum_{k=0}^{2}\theta^{\mathrm{p}}_{t-k}\mathrm{PPI}_{ilt-k} + \sum_{k=0}^{2}\theta^{\mathrm{m}}_{t-k}\mathrm{CPI}_{lt-k} + \gamma_l \\
&\quad \times \text{trend}_t + e_{ilt}, \qquad (18)\\
\text{Output conflict}_{ilt} &= \alpha_i + \sum_{k=0}^{2}\theta^{\mathrm{pf}}_{t-k}\mathrm{PPI}^{\mathrm{food}}_{ilt-k} + \sum_{k=0}^{2}\theta^{\mathrm{pc}}_{t-k}\mathrm{PPI}^{\mathrm{cash}}_{ilt-k} + \gamma_{lt} + e_{ilt}.
\end{aligned}$$

The first two are analogous to the specifications in equation (17), but 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 3 and 4.

The third specification tests an implication of proposition 3. Here, $\mathrm{PPI}^{\mathrm{food}}$ is the component of the PPI 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 $\mathrm{PPI}^{\mathrm{cash}}$ component picks up the remaining cash crops, such as coffee, tea, and tobacco (capturing P_c from the model). Our model indicates that the lost utility from a negative real income shock (captured in $\mathrm{PPI}^{\mathrm{food}}$) is greater than

[43] 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.

the potential utility gained from a positive shock to the value of appropriation (captured in PPI^{cash}) because of concavity. The empirical implication is that $\theta^{pf} > \theta^{pc}$.

As in the case of factor conflict, we examine the robustness of our results to the inclusion of cell-level controls for an oil price index, a mineral price index, and various weather controls, as well as year fixed effects.

V. Results

A. *Factor Conflict*

1. Main Results

In table 2, we present results from the specifications in equation (17) for conflict incidence, onset, and offset. In all regression tables, coefficients represent the cumulative impact over three years of a 1 standard deviation rise in a given price index.[44]

Column 1 shows the result of a regression that omits the CPI and includes CYFEs. A 1 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% ($p < .01$), and the CPI increases conflict by 8.6%. The CPI effect has p-values of .134 with Conley standard errors and .116 with two-way standard errors. In column 3, we add year fixed effects for comparison. The CPI estimate is larger but noisier in this specification. In both cases, the PPI and CPI coefficients are significantly different from each other, whether calculated using Conley or two-way clustered standard errors.

In columns 4 and 5, 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 column 6, we add year fixed effects for comparison, finding that the CPI effect rises to 37.7% and is significant at the 10% level with Conley standard errors but not with two-way clustered standard errors.

In columns 7 and 8, 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% ($p < .01$). The PPI and CPI effects are significantly different

[44] 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.

from each other. This is consistent with the idea in proposition 2 that rising import food prices force low-income workers to join armed groups. In column 9, we again add year fixed effects for comparison. The magnitude of the CPI effect is larger but more noisily estimated.

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. Across the nine specifications, all 15 point estimates are consistent with propositions 1 and 2, while the effects of the PPI and CPI are at least marginally significantly different from each other in five of six cases.

2. Robustness

In appendix C.1, we examine the robustness of these main results to a variety of sensitivity tests. In table A3, we cumulatively add (1) cell-level weather covariates and oil prices $\times$ cell- and country-level production indicators and (2) mineral prices $\times$ cell-level mine indicators from Berman et al. (2017) to the specification with year fixed effects. The PPI and CPI coefficients are at least marginally significantly different from each other in seven of the resulting nine regressions, and all 18 coefficients carry the proposed sign. Seven of the nine PPI estimates are significantly different from zero; the other two are marginally significant. The CPI 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 A4); varying the Conley standard error kernel cutoff from 100 to 1,000 km in increments of 100 km (table A5); aggregating the cell area to 1° cells (i.e., by a factor of 4; table A6); adding to that specification controls for the PPI in neighboring cells (table A7); including a cell-year estimate of population as a control variable (table A8); estimating a conditional fixed effects logit model (table A9); weighting the CPI and PPI components by the extent to which crops are traded by a given country (table A10); weighting the PPI by crop yields per hectare (table A11); and including contemporaneous price indices only (table A12).

3. Heterogeneity

We present country-by-country estimates of these two effects on the left-hand side of figure 4. We do this by interacting our price indices by country dummies and plotting the resulting estimates and 95% confidence intervals by effect size. The red line indicates the overall main effect calculated above. The PPI effects are presented in the top-left cell, and the CPI effects are presented in the bottom-left cell. While many countries

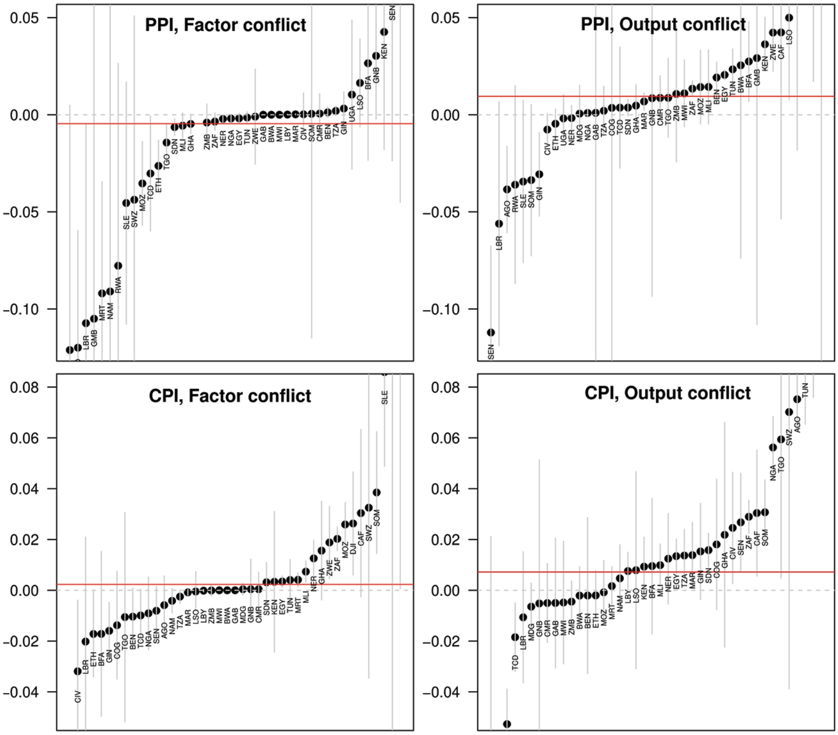

FIG. 4.—Impact of prices on factor conflict and output conflict by country: plot of country-by-country estimates for each of the four conflict-price combinations. They are generated by running either our output- or our factor conflict regression and interacting the contemporaneous and lagged price variables with country dummies. As in the main results, we then calculate for each country the sum of the contemporaneous effect plus two lagged effects and plot the resulting estimates and their standard errors in increasing order of effect size. Each circle represents a country-specific estimate; vertical gray lines are for 95% confidence intervals. The red horizontal line represents the whole-continent estimate reported in the main text.

exhibit large effects that are consistent with the overall main effect, there is nevertheless heterogeneity worthy of investigation.

Our model provides guidance on one source of heterogeneity in the consumer price effect that we can test using subnational data. Recall that higher food prices cause net consumers to join armed conflict groups in part because of the concavity of utility. The soldiering premium is more valuable to a consumer when consumption levels are low, all else equal. A consumer on the margin of violence must be earning a wage lower than that offered by the armed conflict group; they must have few assets for dissaving and little access to credit or insurance. 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 the variable equal to 1 if a grid cell showed nonzero 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 nonagricultural 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 equation (17) that contains $\text{CPI}_{lt} \times \text{Luminosity}_i$, $\text{PPI}_{ilt} \times \text{Luminosity}_i$, and CYFEs, as the interaction generates variation in the CPI at the subnational level. To that end, this exercise serves as both a robustness exercise and a test of theoretical implications. Our model predicts that the 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, the 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 pass-through 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 pass-through 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 pass-through and remoteness/state capacity, we interact the following with the price indices: distance (in 100-km units) to the next nearest lit cell, distance to the nearest port, distance to the nearest land border, and distance to the capital city.[45] 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

[45] Data on the distances from a cell to the nearest border and to the capital city are taken from the PRIO-GRID data set (Peace Research Institute Oslo; Tollefsen, Strand, and Buhaug 2012). Distance to a port is from the SEDAC project introduced above.

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 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 3. The outcome variable in each model is factor conflict incidence. In all six specifications, CPI × Luminosity has a negative coefficient, and PPI × Luminosity has a positive coefficient. Column 1 shows results from a model with luminosity

TABLE 3
UCDP Factor Conflict, Prices, and Luminosity

	Factor Conflict Incidence: 1(Conflict > 0)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Regression Estimates					
PPI	−.0079	−.0510	−.0102	−.0502	−.0083	−.0484
Conley SE	.002	.023	.003	.023	.003	.023
p-value	.000	.028	.000	.030	.005	.037
Two-way SE	.002	.032	.003	.032	.003	.032
p-value	.000	.111	.001	.116	.008	.131
PPI × Luminosity	.0049	.0041	.0072	.0051	.0050	.0032
Conley SE	.002	.002	.002	.003	.003	.003
p-value	.005	.018	.004	.042	.076	.242
Two-way SE	.002	.002	.003	.003	.003	.003
p-value	.007	.019	.010	.073	.098	.272
CPI × Luminosity	−.0040	−.0006	−.0060	−.0031	−.0060	−.0030
Conley SE	.002	.002	.002	.002	.002	.002
p-value	.085	.743	.003	.077	.003	.110
Two-way SE	.003	.002	.003	.002	.003	.002
p-value	.196	.788	.027	.123	.032	.224
	Other Results and Specifications					
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
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	203,962	199,584	203,962	199,584	203,962	199,584

Note.—The dependent variable is UCDP factor conflict incidence. The PPI and CPI are measured in terms of average temporal standard deviations. Reported effects are the sum of price coefficients at t, $t-1$, and $t-2$. Conley SE allow for serial and spatial correlation within a radius of 500 km. Two-way SE allow for serial correlation within cells and spatial correlation across cells within countries. "PPI (CPI) impact" indicates the effect of a 1 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. The models estimated in cols. (2), (4), and (6) also include controls for interactions between each price index and four distance variables: distance (in 100-km units) to the nearest lit cell, to the nearest port, to the nearest land border, and to the capital city. An extended version of this table is included in the appendix as table A3. FE = fixed effects.

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 marginally 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 3–6, however, we see that the CPI interaction effect is larger in (absolute) magnitude and more precisely estimated, ranging from −22% in the baseline specifications (where all four p-values are less than .05) to −11% with the extra set of controls (p-values ranging from .077 to .224).

Taken together, these results support an implication of proposition 2: 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.

B. *Output Conflict: ACLED*

1. Main Results

In table 4, we present results from the specifications in equation (18) for output conflict incidence, onset, and offset. Again, in all regression tables, coefficients represent the cumulative impact over three years of a 1 (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 1 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 column 3, we show that the CPI effect is muted when we add year fixed effects for comparison.

In columns 4 and 5, we see that both indices have large, positive, and significant impacts on output conflict onset (55.7% and 22.9%). The inclusion of year fixed effects in column 6 again results in noisy CPI estimates.

It is clear from columns 7 and 8 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%). Again, the inclusion of year fixed effects mutes the CPI effect.

Table 5 presents results from the lower specification in equation (18), in which the PPI is separated into food crops ("PPI: food crops") and cash crops ("PPI: cash crops"). This allows us to test an implication of proposition 3: that a shock to food crop prices will have a greater impact on output conflict than a shock to cash crop prices.

A 1 standard deviation rise in food crop prices increases the incidence of output conflict by 16.6% ($p < .01$), 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

TABLE 4

ACLED Output Conflict, Combined Producer Prices and Consumer Prices

	Incidence 1(Conflict > 0)			Onset 1(Conflict Begins)			Offset 1(Conflict Ends)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Regression Estimates					
PPI	.0076	.0095	.0090	.0068	.0080	.0078	.0092	.0069	.0057
Conley SE	.002	.003	.002	.002	.002	.002	.004	.006	.004
p-value	.000	.000	.000	.000	.000	.000	.010	.233	.168
Two-way SE	.003	.003	.003	.002	.002	.002	.005	.006	.005
p-value	.007	.000	.001	.004	.000	.000	.044	.243	.236
CPI		.0072	.0013		.0033	.0024		−.1271	.0064
Conley SE		.002	.006		.001	.004		.018	.046
p-value		.000	.824		.009	.590		.000	.889
Two-way SE		.002	.008		.001	.006		.019	.050
p-value		.000	.864		.015	.704		.000	.898
				Other Results and Specifications					
PPI impact (%)	15.1	18.9	17.8	47.2	55.7	54.0	1.7	1.3	1.1
CPI impact (%)		14.4	2.6		22.9	16.5		−23.8	1.2
Country × year FE	Yes	No	No	Yes	No	No	Yes	No	No
Year FE	No	No	Yes	No	No	Yes	No	No	Yes
Country × time trend	NA	Yes	Yes	NA	Yes	Yes	NA	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	173,876	158,270	158,270	169,933	154,795	154,795	7,410	6,774	6,774

Note.—The dependent variables are dummies for ACLED output conflict incidence, onset, and offset dummies. The PPI and 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 $t-2$. Conley SE allow for serial and spatial correlation within a radius of 500 km. Two-way SE allow for serial correlation within cells and spatial correlation across cells within countries. “PPI (CPI) impact” indicates the effect of a 1 standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms. FE = fixed effects; NA = not applicable.

TABLE 5
ACLED Output Conflict and Disaggregated Producer Prices

	Incidence 1(Conflict > 0)	Onset 1(Conflict Begins)	Offset 1(Conflict Ends)
	(1)	(2)	(3)
	Regression Estimates		
PPI: food crops	.0083	.0072	.0076
Conley SE	.002	.002	.004
p-value	.000	.000	.033
Two-way SE	.003	.002	.004
p-value	.001	.000	.063
PPI: cash crops	−.0026	−.0014	.0118
Conley SE	.002	.001	.005
p-value	.116	.327	.024
Two-way SE	.002	.002	.007
p-value	.225	.461	.083
	Other Results and Specifications		
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	.000	.000	.519
Two-way *p*-value	.000	.000	.522
Country × year FE	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes
Observations	173,876	169,933	7,410

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 $t-2$. Conley SE allow for serial and spatial correlation within a radius of 500 km. Two-way SE allow for serial correlation within cells and spatial correlation across cells within countries. "PPI impact" indicates the effect of a 1 standard deviation rise in prices on the outcome variable in percentage terms. FE = fixed effects.

onset effects, as the two offset impacts are close to zero and statistically indistinguishable.[46]

2. Robustness

In table A13, we again cumulatively add (1) cell-level weather covariates and oil prices × cell- and country-level production indicators and (2) mineral prices × cell-level mine indicators from Berman et al. (2017) to the specification with year fixed effects. 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

[46] For a visual representation of our results, see fig. A2, which presents quadratic fits of the four main estimated relationships (i.e., each of factor conflict and output conflict on both the PPI and CPI), controlling for country time trends and cell fixed effects.

controls: a 1 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 A14, 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 price 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.

We also show that the results are qualitatively robust to recoding the outcome variable as "riots" only (table A15); varying the Conley standard error kernel cutoff from 100 to 1,000 km in increments of 100 km (table A16); aggregating the cell area to 1° cells (i.e., by a factor of 4; table A17); adding to that specification controls for the PPI in neighboring cells (table A18); including a cell-year estimate of population as a control variable (table A19); estimating a conditional fixed effects logit model (table A20); weighting the CPI and PPI components by the extent to which crops are traded by a given country (table A21); weighting the PPI by crop yields per hectare (table A22); and including contemporaneous price indices only (table A23).

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 as 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. We therefore interact our CPI with two different measures of urbanization in order to detect whether results are differentially driven by urban unrest.

Results are shown in table A24 and are described in more detail in appendix C.2. Using either an area-based or a population-based definition of whether a cell is "urban," we find that the effect of higher CPI on output conflict remains positive and significant in nonurban 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.

Finally, we investigate the possibility that the contrast we observe between the effects of PPI on factor conflict and those on output conflict are due to differences either in the study periods or in the data collection projects, rather than to the mechanisms put forward in our model. To hold the study period and data sources constant, we use the "type 2" battle in ACLED as a plausible measure of factor conflict, as it records battles after which nonstate armed groups overtake territory. In table A25, we show that, using the same study period, the PPI effect on this measure (−15.0%) is similar to the effect on the UCDP measure (−18.5%) and not similar to the effect on ACLED output conflict (+8.9%). We discuss this exercise in more detail in appendix C.2.

C. *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 data set 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 3 implies that higher food prices will cause net consumers to appropriate output in food-producing areas and 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 III. They ask how often respondents or their family members were victims of (1) theft or (2) 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 that 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 real wages decline, whereas the PPI for cash crops raises the value of appropriable output without causing a 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:

$$\begin{aligned} \text{victim}_{jilt} = {} & \alpha_i + \sum_{k=0}^{n} \phi^{\text{f}}_{t-k} \text{PPI}^{\text{food}}_{ilt-k} + \sum_{k=0}^{2} \phi^{\text{c}}_{t-k} \text{PPI}^{\text{cash}}_{ilt-k} \\ & + \sum_{k=0}^{n} \phi^{\text{ff}}_{t-k} \text{PPI}^{\text{food}}_{ilt-k} \times \text{farmer}_{jilt} + \sum_{k=0}^{n} \phi^{\text{cf}}_{t-k} \text{PPI}^{\text{cash}}_{ilt-k} \times \text{farmer}_{jilt} \\ & + \textstyle\sum_{k=0}^{n} \phi^{\text{ft}}_{t-k} \text{PPI}^{\text{food}}_{ilt-k} \times \text{trader}_{jilt} + \displaystyle\sum_{k=0}^{n} \phi^{\text{ct}}_{t-k} \text{PPI}^{\text{cash}}_{ilt-k} \times \text{trader}_{jilt} \\ & + \mathbb{X}'_{jilt} \zeta + \gamma_{lt} + e_{jilt}, \end{aligned} \tag{19}$$

where victim_{jilt} indicates whether or not an individual j in cell i, country l, and period 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" that the individual is 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_{lt} are fixed effects for country × period; and e_{jilt} is the error term. We cluster standard errors by cell. Our treatment effects of interest for farmers and traders, respectively, are

$$\sum_{k=0}^{n} \phi^{\text{ff}}_{t-k} - \sum_{k=0}^{n} \phi^{\text{cf}}_{t-k} \tag{20}$$

and

$$\sum_{k=0}^{n} \phi^{\text{ft}}_{t-k} - \sum_{k=0}^{n} \phi^{\text{ct}}_{t-k}. \tag{21}$$

Our identifying assumption is that the impact of a food price shock on commercial food farmers is different from that of a cash crop price shock on commercial cash crop farmers only because food prices deflate consumers' wages rather than raising the value of appropriable output, conditional on the covariates listed above. We predict that effects (20) and (21) are greater than zero.[47]

[47] 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, where each period is one-half of a

Results.—We display the results from our estimations of equation (19) in table 6. The outcome variable is an indicator for theft in the first three columns and an indicator for physical attack in the next three. In columns 1 and 4, we estimate a variant of equation (19) that includes the CPI, country fixed effects, and a country time trend instead of cell fixed effects and the country × period fixed effects. In columns 2 and 5, we add time fixed effects (at the level of the half-year). In columns 3 and 6, we estimate equation (19). We present the treatment effects from (20) and (21) in the second panel, together with each effect expressed as a percentage of the dependent variable means.

Focusing on commercial farmers, we see that the impact of food crop prices relative to cash crop prices is positive and large across all six specifications. A 1 standard deviation rise in food prices increases the probability that a commercial farmer experiences theft by 14.7% ($p = .005$) in the baseline specification, 15% ($p = .004$) with added period fixed effects, and 13.7% ($p = .007$) in our preferred specification with country × period fixed effects. The respective equivalent impacts on violence against farmers are 18.4% ($p = .02$), 17.5% ($p = .028$), and 12.9% ($p = .095$). The effect of the CPI is indistinguishable 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 1 standard deviation rise in food prices increases the likelihood that traders report being victims of theft by 9.1% ($p = .1$). While the effect on physical attacks is comparable in magnitude (8%), it is much less precise ($p = .56$).

These results provide support for our theoretical prediction. Higher food prices substantially increase the likelihood that commercial farmers will experience theft and violence in food crop cells relative to equivalent changes to cash crop prices in cash crop cells. Traders are also more likely to experience theft, but not violence.[48]

D. *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

calendar year. This increases our temporal data points from nine to 13. We adjust lags accordingly in regressions so that the sum of effects over two years is presented, as in the cell-level analysis. Second, we facilitate the inclusion of cell fixed effects by aggregating cells from 0.5° × 0.5° to 1° × 1°. 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.

[48] We point readers to a number of complementary exercises in the appendix. In table A26, we show that an increase in the CPI increases self-reported poverty, while an increase in the PPI reduces self-reported poverty for farmers only. In table A27, 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. Finally, in table A28, we show a placebo test in which the main results do not hold for noncommercial farmers.

TABLE 6
AFROBAROMETER OUTPUT CONFLICT: TRIPLE DIFFERENCE

	THEFT			VIOLENCE		
	(1)	(2)	(3)	(4)	(5)	(6)
	Equation (19) Estimates					
PPI: food crops	.0027	.0026	.0017	−.0000	.0000	−.0003
SE	.002	.002	.002	.001	.001	.002
p-value	.165	.188	.291	.970	.977	.875
PPI: food crops × farmer	.0014	.0012	.0008	.0011	.0009	.0000
SE	.002	.002	.002	.001	.001	.001
p-value	.459	.512	.679	.368	.460	.995
PPI: food crops × trader	.0041	.0041	.0046	.0020	.0020	.0022
SE	.002	.002	.002	.001	.001	.002
p-value	.086	.087	.060	.172	.180	.141
PPI: cash crops	−.0023	.0086	−.0089	.0053	.0019	−.0212
SE	.013	.014	.027	.010	.011	.021
p-value	.855	.536	.744	.587	.866	.317
PPI: cash crops × farmer	−.0447	−.0456	−.0422	−.0229	−.0220	−.0169
SE	.015	.016	.015	.010	.010	.009
p-value	.004	.003	.005	.017	.023	.074
PPI: cash crops × trader	−.0319	−.0326	−.0237	−.0126	−.0116	−.0082
SE	.017	.017	.017	.018	.018	.018
p-value	.058	.052	.158	.477	.512	.642
CPI	.0006	.0017		−.0005	−.0011	
SE	.002	.002		.002	.002	
p-value	.742	.422		.744	.516	
	Estimated Treatment Effects in (20) and (21)					
(PPI Food − PPI Cash) × farmer	.0461	.0469	.0430	.0240	.0229	.0169
SE	.016	.016	.016	.010	.010	.010
p-value	.005	.004	.007	.020	.028	.095
Impact on farmers (%)	14.7	15.0	13.7	18.4	17.5	12.9
(PPI Food − PPI Cash) × trader	.0360	.0367	.0284	.0146	.0136	.0105
SE	.017	.017	.017	.018	.018	.018
p-value	.036	.032	.100	.417	.449	.560
Impact on traders (%)	11.5	11.7	9.1	11.2	10.4	8.0
	Specifications					
Country × half-year FE	No	No	Yes	No	No	Yes
Country × time trend	Yes	Yes	NA	Yes	Yes	NA
Half-year FE	No	Yes	NA	No	Yes	NA
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Area FE	Country	Country	Cell	Country	Country	Cell
Observations	39,873	39,873	39,036	39,925	39,925	39,090

NOTE.—The dependent variables are binary responses to survey questions that ask whether individuals over the previous year have been victims of theft (cols. 1–3) or physical assault (cols. 4–6). The PPI and CPI variables are measured 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). Reported effects are the sum of coefficients on price variables at t through $t-4$, 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. SE allow for serial and spatial correlation within 1 degree cells. "PPI impact" indicates the effect of a 1 standard deviation rise in prices on the outcome variable in percentage terms. FE = fixed effects; NA = not applicable.

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 2 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 (2018) 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 the spatial lag is remarkably stable and provides the overall effect of a single-year price shock over time and space (fig. A3).

Figures 5 and 6 show results from versions of our main specification that include temporal lags and leads as well as spatial lags with annuli (concentric circles) up to a radius of 500 km. In the top four plots of figure 5, we show the cumulative effect of adding up to five lags in separate regressions. The cumulative effect becomes larger as lags are added. In the bottom four plots, we plot the individual and combined effects in a regression with four lags and two leads. In the top panel of figure 6, we plot the cumulative effect of adding up to 500-km spatial lags, and in the bottom panel we plot the individual effects of each additional 100-km lag.

As in our simulation, coefficients on individual lags and leads 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: allowing own-cell effects to persist up to 5 years roughly doubles the effect sizes for both factor and output conflicts, and allowing a price shock in one cell to have effects up to 500 km away also roughly doubles estimated overall effect sizes.

E. *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.[49]

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

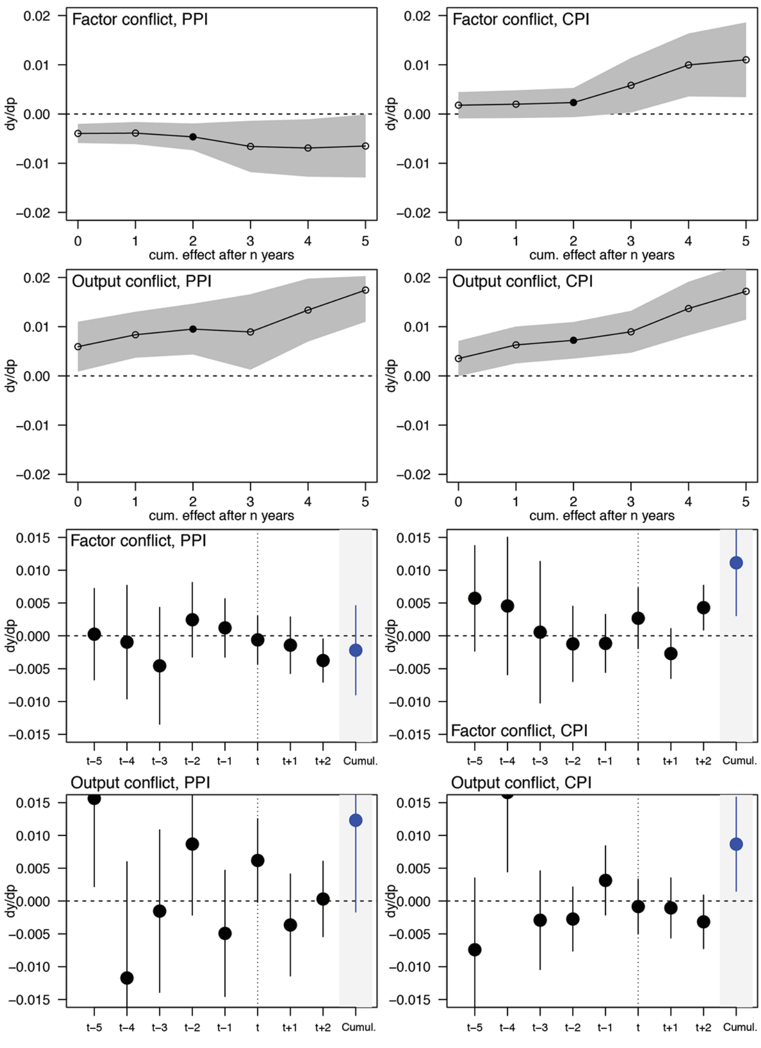

Fig. 5.—Temporal structure of food prices' effect on conflict. *Top four plots*, cumulative (cum.) effect of food price shock after n years. Each circle is from a separate regression and shows the estimated cumulative effect of contemporaneous and lagged effects after n years, that is, $\Sigma_{t-n}^{t}\beta_t$. The shaded area shows the 95% confidence interval. Our baseline specification in the main text is the cumulative effect after 2 years, i.e., $\Sigma_{t-2}^{t}\beta_t$, and is shown as the filled 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 four lags and two leads. Black circles show the point estimate, with the 95% confidence interval, for individual coefficients. The blue circles (farthest to the right) show the cumulative (cumul.) effect of contemporaneous and lagged effects.

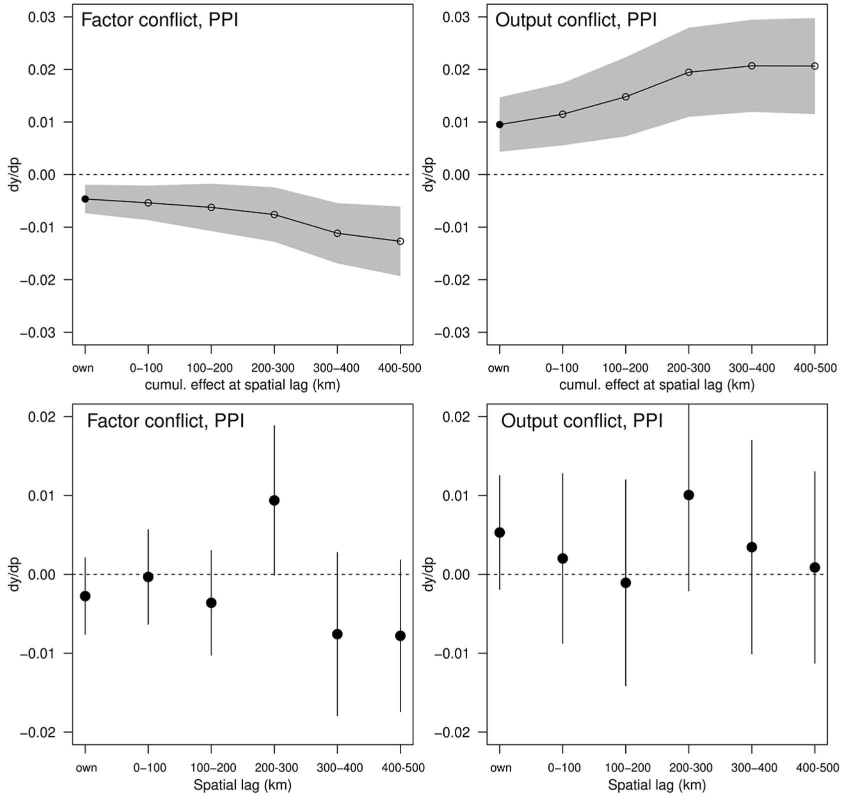

FIG. 6.—Spatial structure of food prices' effect on conflict. *Top*, cumulative effect of a 1-SD producer shock in a given cell on conflict up to 500 km away, for factor conflict (*left*) and output conflict (*right*). Each circle is from a separate regression and shows the estimated cumulative (cumul.)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

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 CYFEs in every specification.

We present the exercise and discuss the results in detail in appendix C.6. Our main finding is that both the CPI and the PPI have markedly diminished effects (in absolute terms) on factor conflict in cells associated with a higher degree of political centralization. The PPI effect changes from −30.3% of the mean to −6.6%, implying an interaction effect of +23.7%. The CPI interaction effect is −17.1%. With output conflict as the outcome, we see no significant effect of the PPI interaction. We also see that 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 price shocks on large-scale factor conflict battles, but not on output conflict events.

F. Naïve Estimates

In our main analysis, we make critical distinctions between what can be defined broadly as consumer effects and producer effects of crop prices on violence. We implement this empirically in two ways: (1) harnessing cell-level data to separate the impacts of producer prices and consumer prices and (2) 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.[50] 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 PPI and CPI. This reflects a common approach taken to estimate the impacts of producer and consumer price shocks on country-level conflict, respectively.

As shown in the first column of panels A and B in table 7, none of the estimated effects on UCDP conflict are distinguishable from zero at standard confidence levels. The null effects are due to the omission of the

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

TABLE 7
Summary of Naïve Regression Results

	UCDP Conflict	ACLED Conflict
	A. PPI	
PPI	−.0174	.0123
SE	.023	.011
p-value	.449	.254
Impact (%)	−3.6	1.4
	B. CPI	
CPI	.0195	.0239
SE	.032	.012
p-value	.544	.056
Impact (%)	4.0	2.6
	C. Both Indices	
PPI	−.0375	−.0027
SE	.026	.016
p-value	.160	.869
Impact (%)	−7.7	−.3
CPI	.0428	.0259
SE	.040	.018
p-value	.292	.154
Impact (%)	8.8	2.9

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 $t-2$. SE are clustered at the country level. "Impact" indicates the effect of a within-cell 1 standard deviation rise in producer (consumer) prices on the outcome variable in percentage terms.

"opposing" price variable and loss of variation caused by the country-level aggregation of the conflict variable. 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 naïve regression is −3.6% ($p = .449$); in the full country-level version it is −7.7% ($p = .16$); and in the full cell-level specification it is −17.2% ($p = .001$).

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 (2018). In panel A, the PPI effect is positive but indistinguishable from zero. In panel B, the CPI effect is positive and marginally significant ($p = .056$). In either case, we cannot distinguish between three competing mechanisms: the consumer price impact on factor conflict, the consumer price impact on output conflict, and the producer price impact on output conflict—in effect, any combination of the three propositions that predicts a positive sign is plausible. 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 analyses leads to a misrepresention of the relationship between world food prices and conflict in Africa.

VI. Discussion and Conclusion

A. *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 the one that 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 nonzero production, we estimate an Africa-wide average effect of the 2004–8 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 (Brückner and Ciccone 2010; Dube and Vargas 2013; Bazzi and Blattman 2014; Berman and Couttenier 2015; Fjelde 2015).

In the second exercise, we apply 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, largely as a result of continued global economic and population growth on the demand side and 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.

Using these projections, we estimate that the change in grain prices from 2010 to 2050 will generate a producer price effect on factor conflict of around −12% with climate change and −6% without. At the same time, higher prices will generate a consumer price effect on factor conflict of +17% (+9%). 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 +10%, about half of which can be explained by climate change. This is demonstrated in the top panel of figure 7.

The bottom panel of figure 7 presents the projected impact on output conflict. The producer price effect is +11% with climate change and +5% without. The consumer price effect is +23% (+12%). This implies a weighted average effect of +30%, around half of which is again 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 role of climate change would mute over half of the overall effect.

B. *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), Harari and La Ferrara (2018), and Berman et al. (2017), 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 provide an incomplete picture.

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

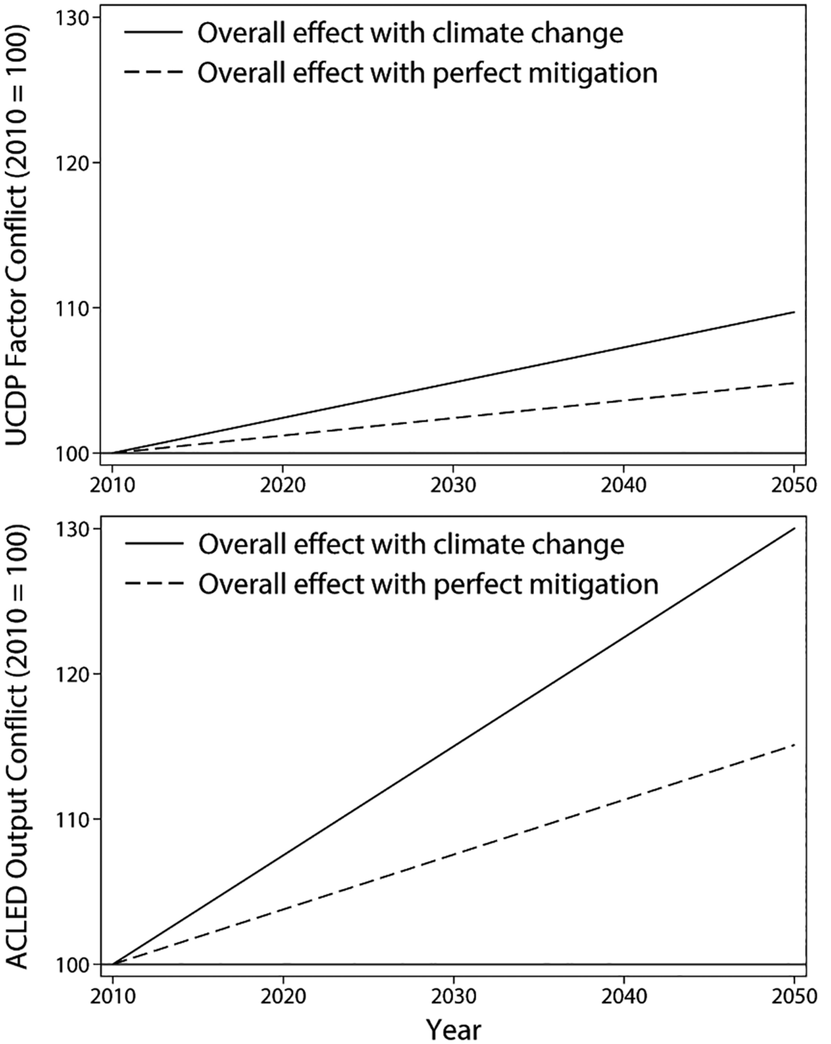

FIG. 7.—Impact of projected change to maize, rice, and wheat prices from 2010 to 2050. Price projections are from the IFPRI (Nelson et al. 2010). The perfect-mitigation scenario assumes that all greenhouse gas emissions cease in 2000 and the climate momentum in the system is halted. Unconditional probabilities of factor conflict and output conflict in 2010 are 2.15% and 4.9%, respectively. Both are normalized to 100.

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. 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 this 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 that food price shocks increase self-reported theft and violence perpetrated against commercial farmers. That the micro-level evidence is consistent with the main cell-level analysis is reassuring, particularly in light of the recent emergence of geocoded conflict data sets 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 2004–8 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. 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 of 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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