Food Resources and Strategic Conflict*

Ore Koren†

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Abstract

A growing number of studies draw linkages between violent conflict and food scarcities. Yet, evidence suggests that within states, conflict revolves around food resources abundance. I develop an explanation for how the competition over food resources conditions the strategic behaviors of three actors: rebels, civilian producers who grow crops, and state forces. Using a statistical-strategic model, I validate my theory at the subnational level on new high specificity spatial data on staple crop access and productivity in Africa for the years 1998-2008 (and use the estimates to forecast conflict on out-of-sample data for 2009-2010). In line with theoretical expectations, local variations in food productivity have a positive, statistically significant, and substantive effect on the strategic behaviors of different actors. These findings suggest that the imperative for food denial as a micro level tactic in civil war should be more seriously incorporated into the work of scholars and policymakers.

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†Department of Political Science, Indiana University, Bloomington, IN, 47405. Email: okoren@iu.edu.

The use of food denial as a macro level strategy in war has attracted ample attention (see, e.g., Downes, 2008; Keller, 1992). Yet, our understanding of how food denial affects conflict patterns at the *micro* level remains poor. In developing a theory that emphasizes the strategic incentives of multiple actors and deriving a strategic empirical model tested on new high-resolution data on food productivity, the present article undertakes the first evaluation of food denial's role as a salient tactic in contemporary civil war.

Understanding how the imperative for food denial can drive different actors to instigate violence is important given that evidence from countries as diverse as Uganda (Mkutu, 2001), Peru (Walker, 1999), and India (Sundar, 2007) suggests that conflict dynamics are closely associated with food resources. As civil war is arguably most prevalent in the developing world, which is also expected to bear the brunt of climate change's effects (Miguel, Satyanath and Sergenti, 2004), it is not surprising that a growing number of studies draw links between environmental conditions such as the variability in temperature or precipitation and violent conflict, hypothesizing that these factors, among others, affect conflict by negatively impacting food production (Miguel, Satyanath and Sergenti, 2004; McGuirk and Burke, 2017; Von Uexkull et al., 2016).

Despite these contributions, little analysis concerning *how* food resources affect violent conflict has been conducted. Some scholars of the climate-conflict nexus argue that decreases in agricultural output can lead to more labor flexibility, which results in cheaper labor and more recruits being available to rebels (McGuirk and Burke, 2017; Fjelde, 2015). However, the focus on scarcity alone cannot predict where conflict over food will arise within the state. For instance, Koren (2018) shows that, at the local level and after accounting for the inherent endogeneity between the conflict and food productivity, the frequency of violent attacks increases during years of higher, not lower productivity. Similarly, McGuirk and Burke (2017) associate abundance and low food prices with conflicts over agricultural inputs. Indeed, a close examination of data on rebel attacks at the *disaggregated* within-country "grid-cell year" level in Africa (Raleigh et al., 2010),[1] shows such attacks predominately target regions where food is grown (92% of all incidents). Fitting explanations should therefore account for how food resource abundance, in addition to food scarcities, affects local conflict frequency (Butler and Gates, 2012; McGuirk and Burke, 2017).

What impact does food security have on patterns of conflict within developing states? How do food resources shape the behaviors of both armed groups and civilians in civil war? To answer these questions, I develop a complementary explanation to scarcity-centric theories, which emphasizes the strategic incentives of actors not only to secure food resources during civil war, but also to *prevent* them from being consumed by others. When pro-state forces – be they the military or ethnic militias – are able to secure more food resources, they can support more troops, reduce the chances of animosity between individuals, and operate in large contingents. This is especially true for countries where troops are paid with staples, such as Sierra Leone during the civil war (Koren, 2018). To achieve strategic advantage, rebel groups might seek to cut off the supply of state forces, which must also rely on locally-sourced food, in order to weaken them. This incentive should give rise to violence not only between rebel and government troops, but also between rebels and local militias defending the civilians where official state militaries lack the capacity to do so (Adano et al., 2012; Hoffman, 2007). In the developing world, where the majority of armed groups are unlikely to receive regular logistic support and must rely on the local population for food (Koren, 2018; Hendrix and Brinkman, 2013), the possibility that conflict will arise over the imperative to deny food support is especially likely.

In developing this argument, I emphasize not only the role played by state forces and rebels, but also by local civilians, the primary producers of food. Building on previous work (e.g., Butler and Gates, 2012; Fjelde, 2015), I posit that when the local civilians raise food support levels, they correspondingly increase the probability the state will win. Moreover, because it varies annually, this level of support cannot be known to the rebels in advance. During war, the rebels anticipate that if more food support is available to state forces, their own chances of victory will diminish. Above a certain level of state forces strength, the possibility of high food support levels becomes a grave threat. This, in turn, gives the rebels an incentive to escalate conflict into regions with more food resources in order to cut state forces off from these sources of support, and increase their (the rebels') chances of victory.

Building closely on past research (e.g., Signorino, 1999; Carter, 2010), I use this theoretical argument to derive a statistical-strategic model that identifies the specific conditions affecting the conflict gains of rebels on the one hand, and civilian producers and their state defenders on the other. Briefly, this strategic approach expands on standard (linear) methods by incorporating not one but two related phenomena of interest, corresponding to attacks and responses. I then estimate this model on high resolution data on conflict and local food access and productivity for the years 1998-2008 (Ray et al., 2012; Ramankutty et al., 2008).[2] Overall, this study provides new and nuanced evidence that food productivity have a strong effect on the strategic calculi of different armed and unarmed actors, which generates intensified preemptive competition over areas with more food resources.

Food Support and Conflict Escalation

Background

The notion that climatic variability affects armed conflict has received much consideration in recent years (e.g., Burke et al., 2009; McGuirk and Burke, 2017; Von Uexkull et al., 2016). This, in essence, is a *labor-centric* perspective: decreases in agricultural output caused by prolonged heat waves or drought can lead to more labor flexibility, which results in cheaper labor and more recruits being available to rebels. For instance, McGuirk and Burke (2017, 26) focus on how variations in food prices alter the opportunity cost of violence and affects the incentives for conflict, and find that food price shocks, e.g. due to drought, "increase self-reported theft and violence perpetrated against commercial farmers relative to equivalent changes in cash crop prices." Similarly, Fjelde (2015) combines static data on local cropland with country level prices to identify local effects of food price variability on civil war. Fjelde (2015, 531) finds that "negative changes to the value of local agricultural production increases the risk of armed conflict in Africa," presumably because "conflict risk increases individual incentives to rebel as opportunity costs go down" and operates by "weakening the state's coercive capacity." More cautiously, Von Uexkull et al. (2016, 12394-12395) find that ongoing conflicts "decrease the local population's ability to cope with increased environmental hardship and increase their incentives to sustain ongoing resistance," but also emphasize that, "it is clear that drought explains a small share of the observed variation in conflict involvement, implying that the substantive effect is modest compared with central drivers of conflict."

As useful as the labor-centric perspective is, it also overlooks the key fact that a larger pool of potential recruits means little if the rebel group cannot provide them with adequate food support. Therefore, an increasing number of studies that focus on the *subnational* level now emphasize that within violence-prone countries, conflict might be more likely to arise in areas with more food resources (e.g., Butler and Gates, 2012; Adano et al., 2012; Koren, 2018). These studies highlight the importance of locally-grown resources to maintaining and improving the wellbeing and fighting capacity of different groups in many (rural) regions of the developing world. They also identify numerous reasons for why conflict might arise in food-abundant areas, including the need to secure resources for self-sustenance, satisfy demand for particular resources such as staple crops or cattle, or control access to water.

In line with this research, rather than focusing on labor the present study emphasizes the importance of food as a crucial resource of fighting. However, its key motivation is that despite the valuable insights provided by both bodies of research, we are still missing a theory that (i) explains when strategic interactions around food-related concerns shape broader conflict patterns between different armed and unarmed actors, and (ii) identifies, isolates, and verifies specific causes for why conflict concentrates in food-abundant areas. Indeed, to explain these interactions and the trend, shown in the introduction, that rebel attacks concentrate in areas with more food crops, I design my theory around the competition over food resources. In this context, food (in)security relates to the (in)ability of actors, armed groups and communities, to secure adequate amount of and/or access to food (Barrett, 2010). Correspondingly, to weaken one's rivals, possessing and even destroying sources of food is a beneficial strategy that increases the opponents' levels of food insecurity, thus negatively affecting their fighting capacity (Hendrix and Brinkman, 2013).[3]

Basic Concepts

When will rebels benefit from escalating conflict into a given region in a given year (t), and when will the civilians be able to increase the probability that such attacks will be thwarted? Building on the evidence that the interactions over food denial during civil war arise strategically, we can derive a two-step testable theory to answer these questions.[4]

Assume three actors interacting in an agricultural region of a developing country: a set of civilians (i.e., food producers) who work the land to grow crops and livestock; rebels, who seek to attack food-producing regions if doing so would weaken their enemy; and state forces (ethnic militias, civil defense forces, government troops, etc.) who rely on the civilians for food support. During war, the civilians decide the amount of food they provide to the state forces, which the rebels cannot know in advance. Because the civilians decide their level of food support prior to being attacked, the rebels will always be concerned that areas with more food productivity will improve the state forces' chances of victory.[5] As recent studies illustrated (e.g., Koren, 2018; Hendrix and Brinkman, 2013), the probability that the state will defeat the rebels is a function of the state forces' military strength *and* the effect of local food support on increasing the fighting capacity of state forces. The effect of food support is also influenced by other factors, such as how much escalating conflict into the region will harm food support levels, considering their importance to the state forces.

During war, the rebels seek to target locations where food resources are grown and stockpiled to control these areas and prevent state forces from using them for their own consumption. In some cases, especially if the amount of food needed to support the troops is relatively low, these attacks might also be intended to force the civilians to withdraw their support from the regime, and to deprive the state of potential tax revenues (Wood, 2010), which in rural areas closely correspond to agricultural productivity (Fjelde, 2015).

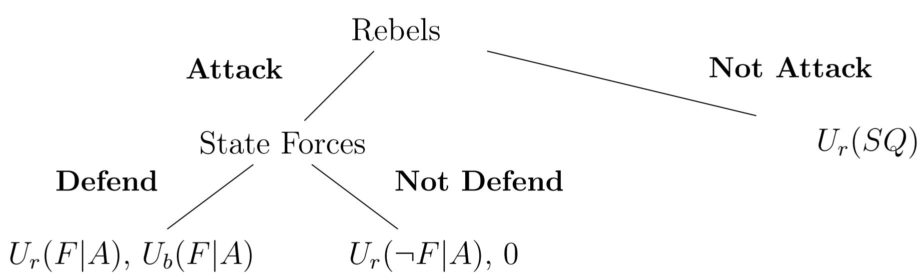
However, attacking can be costly to the rebels, for instance due to the need to mobilize fighters and obtain additional munitions, and because these attacks can result with the loss of fighters and equipment. Attacking a given region can thus be costly and, if the rebels lose, possibly detrimental. Hence, the rebels might choose not to attack, but rather maintain their current war effort levels (or lack thereof), or – in other words – adhere to the status quo. Under said status quo, the rebels get to keep their resources rather than risk the costs of attacking the state's food breadbasket territories. Yet, if they attack and conquer an agricultural region, the rebels gain control both of the land and the food produced therein, and other rents (e.g., taxation, lucrative resources).

As discussed in the next section, the civilians' choice of support is directly shaped by variations in food availability within the region each year. Importantly, during civil war, the civilians not only might incur a cost due to loss of lives and property, but also face the opportunity cost of allocating food to support state forces rather than using it for other purposes, such as selling it on the market or using it for their own consumption. However, if providing food support pays off and the state forces successfully defend them from the rebels, the civilians get to keep the entirety of the land, even if not all the food produced on it during a given year. However, if the rebels attack and the state forces lose or fail to defend the civilians, then the civilians must forfeit their land, or else switch to feeding the rebels to avoid retribution (see, e.g, Wood, 2010; Hultman, 2009).

According to this logic, the state forces' decision whether to fight (harder) against the rebels in a given region directly reflects the civilians' actions. If the rebels choose to attack to hurt the state's food support levels, then state forces will be much more likely to face rebel attacks where and when the civilians can offer more food support. Therefore, the variation in the probability of state response reflects right-hand side factors corresponding to the civilian producers' behaviors in the strategic-statistical model discussed in the next section. Considering the importance of this assumption to my argument, I control for alternative explanations not only in the models reported here, but also in the sensitivity analyses discussed in the Supplemental Appendix.

To help visualize the strategic nature of these dynamics and how each action affects the different actors' gains – or utilities – I plot the sequence of moves expected by my theory in Figure 1 below. In this plot, the rebels first decide whether to attack a given region or not during a given year. Correspondingly, knowing the level of support they might obtain from the civilians in this regions, the state forces decide whether or not to defend the civilians based on on food support availability and whether or not the rebels escalate their war efforts.[6]

Figure 1: Strategic Interactions and Player Utilities



Theoretical Expectations

A key feature of the argument developed here is that localized conflict might arise *endogenously* as a consequence of the strategic choices made by the civilian producers on the one hand, and the rebels on the other. The purpose of the theory developed here and the empirical strategy discussed in the next section is to focus on both causal arrows in this endogenous relationships, namely how food access influences rebel attacks, and how both food productivity and attacks influence defense force responsiveness. Beginning with the latter, securing more food allows state forces to recruit and support more individuals, operate in larger contingents and improve their operational durability, while higher yields of staple crops can be converted into state revenue and used to buy weapons and equipment (Koren, 2018). As such, higher levels of food support increases the state's overall fighting capacity, and thus the probability of winning the war. More specifically, the civilians' might choose to provide support under three conditions.

First, when state forces are stronger, providing food support is more likely to pay off. Stronger state forces have a higher probability of winning, which also means that the possibility of rebel retribution – potentially an important deterrent for supporting the state – is lower (Wood, 2010; Hultman, 2009). Better-trained and better-supported state troops are also more likely to possess higher fighting and mobilization capacity, and hence be more responsive to rebel attacks.

Second, (more) food support will increase the probability of state defense when it greatly improves the state forces' fighting capacity, especially considering that the effects of food support might vary across different armed groups. A good example is that of civil defense forces (CDFs), which – in many civil war contexts such as Sierra Leone (Hoffman, 2007) and Iraq (Mowle, 2006) – are formed and supported by the local civilians. Because these groups are relatively poorly-trained but at the same time heavily embedded in local social networks, even a small amount of food provision can facilitate great improvements in fighting capacity and troop recruitment (Hoffman, 2007). In contrast, well-supported military troops have the advantage of being able to mobilize food contributions from other regions, which means that – while they do rely on food contribution by local civilians to their fighting efforts – the marginal returns from food produced in a given region are lower (Koren, 2018) compared with unsupported forces, which often must live off locally-supplied food.

Finally, recall that when the rebels decide to target a given region to control the food resources produced therein, they rely on the land's productivity to define whether these regions are important to state forces (Koren, 2018). Correspondingly, the state has a stronger incentive to protect areas with more valuable and more fertile land. Moreover, the civilians can also grow and allocate more food support to the state in such regions, meaning they have better means of protecting it (conditional on weather patterns).

Identifying some conditions under which the civilians will increase food provision serves as the basis for establishing why the rebels may choose to preemptively attack regions with more food resources. Recall that when the civilians provide more food support, they improve state troops' ability to operate for longer periods of time, recruit more troops, and operate in larger contingents. Food support is also a finite resource because the civilian producers cannot provide more food than they can physically produce and stockpile due to limitations in infrastructure that force communities and individuals across the developing world to rely on food produced locally (Butler and Gates, 2012; Adano et al., 2012; Koren, 2018).

As a result, in deciding whether or not to attack a give region to harm the state's source of food support, the rebels will realize the civilians residing in regions with more arable land will always allocate some of these resources to support state forces, and hence that higher levels of food support are a credible threat. More allocations decrease the rebels' overall probability of victory, and it is this intuition that explains why they would choose to attack regions with more food crops. There are two explanations for this logic.

The first is *effective resource allocation.* Attacking a region to preemptively weaken state forces becomes an especially attractive strategy if violence has a strong impact on reducing available food supplies during war, especially in regions that are sizable producers of food and are hence crucial to the state's fighting efforts. Correspondingly, by attacking and conquering such regions, or – in extreme cases – laying them to waste, the rebels will deal a painful blow to the state and its forces. Therefore, choosing to attack a region where more food is grown will give the rebels more "bang for their buck" compared with attacking regions where less or no food is grown, all else equal. This, in turn, explains why the rebels' strategic calculations are likely to be affected by food resource-related concerns, and hence why preemptive violence over food resources – during civil war or otherwise – might be more prevalent, perhaps, than initially expected: assuming a similar levels of investment, it pays more to target productive areas.

The second explanation relates to *impact benefits.* If by attacking food-abundant regions the rebels are able to cause greater harm to the state forces, then they might choose to attack even in regions where the state is relatively strong, which would otherwise serve to deter attacks. If state forces are more likely to come to the aid of civilians in regions that contribute more food provisions, then the rebels will also be more likely to attack where they perceive food support levels to be higher. Thus, the more effective a tactic attacking food-abundant regions is in weakening state forces, the more prevalent these attacks will be.

Anecdotal evidence supports these claims. For instance, RENAMO, a rebel group in Mozambique, systematically sought to weaken the government by attacking rural areas and isolating them from the capital, a strategy that emphasized the importance of agricultural production to the regime's war efforts (Hultman, 2009, 826-827). RENAMO thus employed a combined strategy of possession – conquering some areas in the center to secure food for its troops – and preemption – attacking areas to prevent food support from reaching government forces. Therefore, while "[i]n control areas, RENAMO established bases, and the civilian population was exploited and involved more directly in the rebel activities, for example as food producers," villages in the south, i.e., closer to the capital, "were mainly destruction areas, where RENAMO just carried out military operations, attacking villages and killing people" (Hultman, 2009, 832-833).

The strategic-response framework developed here therefore provides one explanation for why, within developing states, conflict tends to concentrate in areas with an abundance of food resources. Rather than thinking of conflict over food resources as a pressure on consumption (Miguel, Satyanath and Sergenti, 2004; McGuirk and Burke, 2017), a useful way of thinking of food's role in war is to theorize it as a weapon. Under this framework, actors seek to control food resources not for consumption to improve their own dietary energy availability or to reward supporters, but rather to worsen their opponents' fighting capabilities by denying them access to food. Food denial has been used repeatedly to weaken and defeat one's opponents throughout history, with some notable instances including the Allied blockade of Germany during World War I (Downes, 2008) and the Ethiopian Derg regime's intentional starvations of Tigre and Eritrea (Keller, 1992). These instance, which show that planned famines can be used as a *macro* level strategy to destroy one's opposition, complement my theory and the partial list of campaigns documented in Table A.1, Supplemental Appendix, which show that food denial can also be initiated as a *micro* level tactic to achieve the same aim during civil war.

The strategic-response framework developed here thus suggests that the civilians will provide some level of food support to improve the state forces' chances of victory, which prompts the rebels to preemptively target these regions in order to weaken the former. The rebels cannot know *ex ante* if the civilians will provide food support to state forces, or how much food will they provide. However, because the rebels can observe how much food is grown in the region, they will prefer to target, on average, food-abundant areas, under the assumption that in these regions more food will be made available to support state forces, and hence that (a higher level of) food support is more likely. Therefore, attacking food-abundant regions will have an especially strong impact on weakening state forces, and thus on improving the gains to the rebels from escalating conflict into the region. This suggests the following expectation:

- **E1:** The likelihood of a rebel attack increases in regions where more food crops are grown

Correspondingly, considering that providing food support always increases their fighting capacity, the state forces will be more likely to defend areas where more support is available. Moreover, the civilians will be more motivated (and more able) to provide higher levels of support in more fertile regions, where they have both more capacity and a stronger incentive to defend by increasing their nutritious food contributions. This is especially true where state forces have a higher chance of defeating the rebels, as food support is more likely to pay off, thus increasing the gains of defending against an attack. This suggests the following expectation:

- **E2:** In regions where and years when the civilians can provide higher levels of food support, the likelihood that state forces will fight the rebels increases

Empirical Analysis

Identification

To effectively model the different outcomes presented in Figure 1, an approach is needed that can incorporate factors influencing both the likelihood of rebel attacks, *and* how they interact with the state forces likelihood of defending a given region during a given year *simultaneously*. A standard model for binary data (e.g., logit) can model only one of these at the same time, either factors influencing the rebels decision to attack, or the determinants of the state forces' decisions to protect. Yet, as was discussed above, the process of attacks and defenses is *endogenous* (Signorino, 1999), as a defense cannot occur without the rebels attacking first, while food support can impact both outcomes in different ways. Effectively modeling Figure 1 requires a strategic-statistical approach that expands on standard single-dependent-variable methods by incorporating not one but two related phenomena of interest, corresponding to attacks and responses.

This statistical-strategic model ensures that the interactive nature of attacks and defenses as affected by food resources availability and access is adequately operationalized and – importantly – that the model is correctly identified with respect to these dynamics (Signorino, 1999). Like standard regression approaches, the strategic logit equivalent of the two-step argument developed in the previous section necessitates making the plausible assumption that all actors operate rationally within limitations (i.e. bounded rationality), and that they hence operate with some error (e.g., Signorino, 1999). This allows me to model the decisions occurring at different nodes of Figure 1 – i.e., whether to attack or defend given an attack – as two different-yet-related stages of the same statistical model using an approach called logistic quantal response equilibrium solution concept (LQRE) (Signorino, 1999; Carter, 2010). A special case of the LQRE in which there is no uncertainty is used to identify each player's utility equation. This empirical model is thus structurally consistent with my theoretical argument, but also accommodates errors to be made by the different actors.

Note that while the use of LQRE in the discipline has been constrained largely to formal modeling, such formalization is not necessary for the LQRE model to be applied, as this approach is inherently empirical (Signorino, 1999). As long as a set of discrete outcomes exists, and as long as these follow some form of a strategic or sequential logic (as described in Figure 1 and discussed in detail above), then the empirical model used to test this two-step logic can be estimated using LQRE. In Figure 1, there are four discrete outcomes – the rebels attack or not, and the state defends or not – under the logic that the choices made by each actor reflect deviation from a path where food support is held constant, or in formal terms, the equilibrium path. As Signorino (1999, 294) explains, "[t]he LQRE solution concept applied here is a promising approach for incorporating the structure of theorized strategic interdependence into statistical models." The two-step LQRE model is thus used to overcome a misspecification issue caused by relying on the standard logit model, i.e., a model that does not take into account the strategic nature of interactions over food support, as shown empirically below.

The statistical-strategic model thus captures the idea that the rebels and state forces each make decisions during war by weighing their expected gains from each possible action (their utilities). In this case, it is useful to begin with the last step in the theoretical model as presented in Figure 1, the decision of the civilians to provide food support and the state to defend, and then move up the tree following each actor's calculations. In the last step, for each geospatial unit (region), $i = \{1, 2, 3...n\}$, during year t, the state needs to decide whether to defend or not in case of rebel attack based on food support levels. This equation captures the probability of state defense in the case of rebel attack given some level of food provision (i.e., if food present, F) compared with the probability of defense when no food is provided (i.e., $\neg F$). Accordingly, if the rebels decide to preemptively attack to deny food resources from the state, then the defenders make the following comparison:

$$
\begin{aligned}
p_{b,i|F} &= U_b^*(F|A) \geq U_b^*(\neg F|A) \qquad (1)\\
&= U_b(F|A) + \epsilon_F \geq U_b(\neg F|A) + \epsilon_{\neg F}
\end{aligned}
$$

We can rewrite these probabilities in logit terms. Assuming the error terms are independent and identically distributed (i.i.d.) Type 1 Extreme Value yields:

$$
\begin{aligned}
p_{b,i|F} &= \frac{exp^{U_b(F|A)}}{exp^{U_b(F|A)} + exp^{U_b(\neg F|A)}} \qquad (2)\\
p_{b,i|\neg F} &= 1 - p_{b,i|F}
\end{aligned}
$$

Equation (2) corresponds to a standard logit, where the dependent variable is the probability of state forces defending during a rebel attack. However, as mentioned above, the two-step theory advanced here assumes that these decisions are inherently dependent in the rebels decision to attack or not and the factors affecting this decision. Accordingly, the statistical model must "nest" these probabilities within the probability that the rebels will attack. Moving up the tree in Figure 1, the rebels make their decision to attack (to play A) or not (to play $\neg A$) by comparing, with some error, the gains from not attacking – i.e., adhering to the status quo, $U_r(SQ)$ – to their utility from attacking. This is calculated by multiplying each of the two possible outcomes by the probability that each is realized, and putting these probabilities in logit terms as required by the LQRE. Assuming, again, that the error terms are i.i.d. Type 1 Extreme Value:

$$
p_{r,i|A} = \frac{exp^{(p_{b,i|F})U_r(A,F)+(p_{b,i|\neg F})U_r(A,\neg F)}}{exp^{(p_{b,i|F})U_r(A,F)+(p_{b,i|\neg F})U_r(A,\neg F)} + exp^{(p_{r,i|\neg A})U_r(SQ)}} \qquad (3)
$$

Additionally, as was mentioned above, the utility of at least one possible outcome at the initial information set for both civilians and rebels is normalized to zero (Signorino, 1999). Hence, in all models reported both here and in the Supplemental Appendix, all coefficients are evaluated with respect to an outcome where the rebels attack (play A), but the civilians *do not to provide food support* (play $\neg F$), which is correspondingly normalized to zero (Signorino, 1999). So, a positive coefficient on, say, crop yields means that providing food support improves the probability of state defense during an attack compared with a situation where food is not available.

The Dependent Variable

Building on previous research into the relationship between food and conflict (e.g., Fjelde, 2015; Koren, 2018), the empirical model is tested on subnational data for all countries in Africa encompassing 11 years (1998-2008) for which information on all variables was available. Africa was chosen as the focus of empirical analysis for three reasons. Firstly, the Armed Conflict and Location and Event Data (ACLED) Version 6 dataset (Raleigh et al., 2010), which provides one of the most exceptional coverages of a wide variety of violent events at the highly localized level, covers exclusively African countries for the period of concern.[7] Moreover, ACLED includes a broad spectrum of dyadic interactions that incorporate not only rebel and military groups but also local militias and CDFs. This facilitates correct identification of my theoretical argument – which incorporates the role of these groups – and ensures that the statistical-strategic model captures a sufficiently high number of heterogeneous localized conflict events.

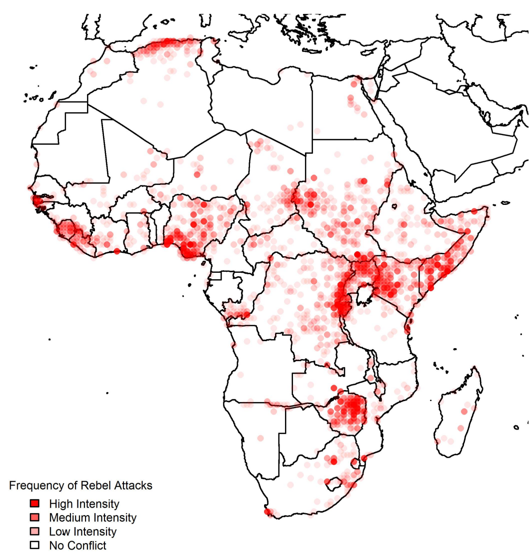
Secondly, the focus on Africa as the world region currently most susceptible to the effects of food insecurity – through climatic variability or otherwise – corresponds to previous studies on climatic variation, food security, and conflict, which similarly focus on Africa (e.g., O'Loughlin et al., 2012; Butler and Gates, 2012; Adano et al., 2012; Koren, 2018).[8] Finally, considering the size of the dataset and the necessity to rely on computer simulations for deriving statistical estimation, any larger sample would have presented significant – and insurmountable, based on available resources – computational challenges.

Unlike in a standard logit model, which includes only one dependent variable, the dependent variable in an LQRE model must capture two highly-codependent phenomena: (i) the decisions made by the rebels to attack or not, and (ii) the decision of the state to defend or not, which with respect to food support is reflected by the civilians' actions. Information from ACLED was used to construct the two-part dependent variables. ACLED draws on (i) information from local, regional, national and continental media reviewed daily; (ii) NGO reports used to supplement media reporting in hard to access cases; and (iii) Africa-focused news reports and analyses integrated to supplement daily media reporting.

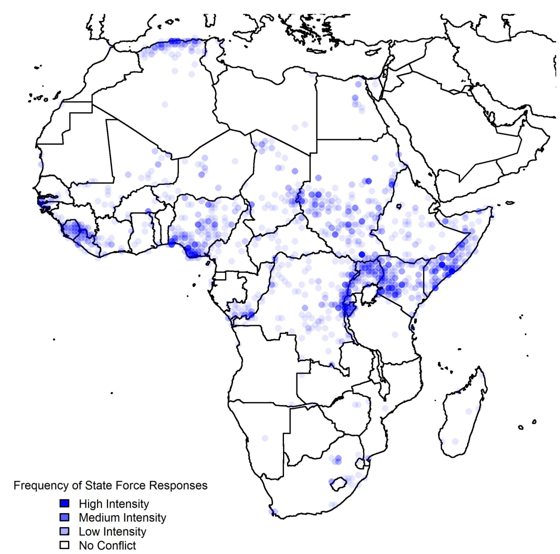
For the first part of the dependent variable, there are two discrete actions for the rebels: to attack (A) or not attack ($\neg A$).[9] The rebels are coded as Attack if they are recorded to *initiate* a conflict (including one sided attacks against civilians) in a given cell during a given year,[10] whether a group identified as state forces was involved or not, not Attack otherwise. Correspondingly, given an attack, the state forces can either defend the civilians against attacks (D) or not ($\neg D$). Hence, the second part of the dependent variable records whether state forces, defined as official militaries, or as pro-government militias and ethnic/local CDFs, as Defend if they are involved in any type of violent conflict initiated by rebels in a given locality during a given year,[11] not Defend otherwise.

Because it is focused on the variation in violence within states, data measured at the annual country level would be inadequate for the purpose of empirical verification. Accordingly, the violent conflict data from ACLED and all other indicators are structured into a cell-year level dataset wherein cells, my cross-sectional unit of interest, are measured at the 0.5 x 0.5 decimal degree resolution – or cells of approximately 55 x 55 kilometers at the equator (3025 square kilometer area) – for all African land areas annually (t) (Tollefsen et al., 2012). Relying on this fine-grain empirical framework allows me to carefully and accurately operationalize the level and variation in food productivity within and across different grid cells, which is necessary for my hypothesis to be evaluated. Thus, this framework is sensitive enough to capture variations in the prevalence of rebel attacks and state forces responses as reflected in the distribution of staple cropland and yield levels across the entire African continent, but not overly disaggregated such that my localized indicators lose their precision levels due to different approaches of measuring a campaign's geographic location (Weidmann, 2013). There are approximately 10,674 cells observed for any given year within the 1998-2008 sample period, with the average country containing roughly 205 cells. The distribution of rebel attacks and state force responses for 1998-2008 are plotted by grid cell for the entire period and annually in Figure 2 below, and their frequencies are reported in Figure A.1, Supplemental Appendix.

Figure 2: The Regional Distribution of Rebel Attacks and State Force Responses by 0.5 ∘ Grids, 1998-2008



Rebel Attacks, 1998-2008



State Responses, 1998-2008

Regressors

The specification of the rebels' decision to not attack (status quo) must include the key variables that influence their decision to initiate localized attacks over food support. First, potential attackers are likely to employ violence in response to previous provocations, or in locations where they have attacked previously (e.g., Buhaug, Gates and Lujala, 2009). Second, lagged indicators of (low) development and political openness have been shown to be consistent predictors of protracted conflict (Von Uexkull et al., 2016). Therefore, to model the rebels' gains from the status quo, historical context indicators impacting their propensity to fight are included in this equation. These indicators include: history of conflict, defined as the number of all political violence-related events by all types of actors, state and nonstate, that occurred in a given cell the previous year (Raleigh et al., 2010); the gross domestic product (GDP) per capita for the previous year (Gleditsch, 2002); and the level of political openness in the previous year as measured by the Polity2 indicator (Marshall, Jaggers and Gurr, 2013). The expectation is that the rebels will be less likely to attack in territories without much history of conflict, as well as in stronger, wealthier, and more democratic countries. Considering that civil war might have a simultaneous relationship with some of these country-level factors, all variables in the status quo utility equation were lagged by one year. The rebel' utility from the status quo is thus modeled as:

$$
\begin{aligned}
U_r(SQ) = \alpha_{SQ} \; + \; & \beta_{SQ,1} Conflict\ (lag)_{it} \; + \; \beta_{SQ,2} GDP\ PC\ (lag)_{it} \; + \\
& \beta_{SQ,3} Polity2\ (lag)_{it} \; + \; \mathbf{\Phi_t}
\end{aligned} \tag{4}
$$

Where α is the intercept; and $\mathbf{\Phi_t}$ are fixed effects by year to account for temporal dependencies.

To measure land productivity and its effects on the rebels' decision to attack a given location in equation (4), I employ a highly localized food access indicator, *Cropland*, created by Ramankutty et al. (2008) (see Supplemental Appendix for more information on this indicator). The researchers utilized two sources of data to create their map. The first source were global satellite-based land cover data obtained from two previous datasets, BU-MODIS and

GLC2000 (Ramankutty et al., 2008, 7-8). The second source were national and subnational census data on cropland area and food inventories. They then used regression techniques to train the satellite land cover data against the census data. The resulting estimates along with the satellite data allowed Ramankutty et al. (2008) to then map cropland areas at the high-resolution 5 minute ($\sim$0.08 $\circ$) level. In the second step, Ramankutty et al. (2008, 11-12) further adjust their high-resolution maps, scaling up or down all pixels within an administrative unit to exactly match the census data. The resulting indicator was aggregated to the 0.5 $\circ$ x 0.5 $\circ$ level via averaging for comparability across cases and provides some of the best available high-resolution data on staple crop production by area. As such, this variable is arguably the best available indicator of the global distribution of staple crops, which is relatively constant within the 11 year period analyzed here, and hence of the land value within the rebels' strategic calculations as hypothesized in the previous section.

While staple crop area provides a useful approximation of where food support is more likely to be available – a rebel concern – it is not necessarily a good indicator of the actual levels of food support provided by the civilians annually in given region. Such an indicator should closely approximate the actual amounts of food that could be *consumed or stored* annually within a given grid cell. It is thus useful for such an indicator to vary annually, as to verify whether higher annual productivity is associated with an increased likelihood of state forces responding to attacks. This also means that using perishable resources such as vegetables to approximate state force responsiveness is less than ideal, and that an adequate indicator of annual food support should – at the very least – be operationalized using food crops that are both more durable, and provide a greater caloric "bang for buck" (Koren, 2018). As the value of food support is, to some extent, dependent on how much food can be produced in a given grid cell, an effective parametrization should capture this codependency.

Therefore, to approximate the level of food support provided by the civilians in a given region during a given year, I rely on an indicator measuring annual wheat productivity by grid cell (Ray et al., 2012). Wheat was chosen because as a staple food for about 35%

of the world's population, it provides more calories and protein in the world's diet than any other crop, and can be stored for relatively long periods of time (Asfaw Negassa et al., 2013). Moreover, in Africa wheat is in exceptionally high demand, which cannot be met by production supply (Asfaw Negassa et al., 2013), making this crop a highly valuable food resource to the state compared with more prevalent resources, such as maize.[12] Indeed, past research illustrated that wheat a strong determinant of conflict in the region (Koren, 2018). Using annual productivity measures, specifically, approximates better the amounts of food immediately available (e.g., in stockpiles) for consumption. This indicator thus provides an exceptional coverage of the annual variations in food support availability at the highly-localized level. Furthermore, by illustrating that the positive relationship between food support and state responsiveness persists over time, this indicator provides a major improvement over past studies of this sort that favored static measures of cropland at comparable levels of geographic resolution (e.g., Fjelde, 2015; O'Loughlin et al., 2012).

Data for constructing this wheat productivity indicator were obtained from Ray et al. (2012), who constructed what is arguably the best high-resolution indicator of wheat productivity currently available, using methods discussed in detail in the Supplemental Appendix. To ensure comparability against other variables used in this study, these wheat data coded by Ray et al. (2012) were summed to the annual 0.5 $\circ$ grid cell level. The resulting $\textit{Wheat Productivity}_t$ variable therefore measures the total wheat hectares harvested within a given 0.5 $\circ$ grid cell during a given year. Importantly, while wheat is arguably the most highly valued food crop, and is hence the best crop to test defense force responsiveness, in Table A.4, Supplemental Appendix I illustrate my findings remain unchanged when the productivity of maize, a more prevalent staple crop (Koren, 2018), is used instead of wheat. For summary purposes, averaged values for *Cropland* and *Wheat Productivity* for the 1998-2008 period are presented in Figure A.2, Supplemental Appendix.[13]

In line with my argument, several additional variables (some of which are not explicitly discussed above) were also included in both equations (5) and (6). These indicators are all measured at the *grid cell* rather than country level, which adequately accounts for the effects of these variables at the highly-localized level. First, an indicator measuring the number of people in a given cell, *Population* (Nordhaus, 2006), is included to account for the potential effect of population densities on the rebels' and civilians' utilities during attacks. Second, an indicator denoting gross cell product in a given year (measured in billion USD), *GCP* (Nordhaus, 2006), is included to account for other economically-productive activities. Because *GCP* might not have good continental coverage in Africa, a third variable measuring average nighttime light emissions within a given cell during a given year, *Nighttime Light*, is added to the models. Past research shows that nighttime light emissions are a useful proxy of economic productivity and development (e.g., Koren and Sarbahi, 2018), and *Nighttime Light* is included to complement the effect of *GCP* and ensure that the models adequately capture the theoretical incentives of both rebels and state forces to fight in areas where more profits can be obtained.[14]

Third, indicators measuring average annual temperature (*Temperature*) and rainfall (*Precipitation*) levels by grid cell are included to control for the effect of these factors on food production and correspondingly on conflict. Next, as rebel groups frequently maintain bases across the border, which provides an advantage in launching attacks closer to borders (Buhaug, Gates and Lujala, 2009), an indicator denoting the distance of a given grid cell to the border (*Border Distance*) is added to equation (5) to approximate rebel group strength. Correspondingly, as my theory suggests that state forces are more responsive in areas closer the state's center of political and economic power (Hultman, 2009), an indicator denoting distance from each cell to the capital was included in equation (6). Summary statistics for all variables are reported in Table A.2, Supplemental Appendix. As was the case in Equation 4, fixed effects for each year are added to the model to account for time-specific dependencies. Thus, the determinants for conflict outcomes are:

$$U_r(AF) = \alpha_{r|AF} \ + \ \beta_{r|AF,1} Cropland_{it} \ + \ \beta_{r|AF,2} Population_{it} \ + \tag{5}$$
$$\beta_{r|AF,3} NighttimeLight_{it} \ + \ \beta_{r|AF,4} GCP_{it} \ + \ \beta_{r|AF,5} Temperature_{it} \ +$$
$$\beta_{r|AF,6} Precipitation_{it} \ + \ \beta_{r|AF,7} Border\ Distance_{it} \ + \ \mathbf{\Phi_t}$$

$$U_b(AF) = \alpha_{b|AF,0} \ + \ \beta_{b|AF,1} Wheat\ Productivity_{it} \ + \ \beta_{b|AF,2} Population_{it} \ + \tag{6}$$
$$\beta_{b|AF,3} NighttimeLight_{it} \ + \ \beta_{b|AF,4} GCP_{it} \ + \ \beta_{b|AF,5} Temperature_{it} \ +$$
$$\beta_{b|AF,6} Precipitation_{it} \ + \ \beta_{b|AF,7} Capital\ Distance_{it} \ + \ \mathbf{\Phi_t}$$

Main Findings

Table 1 first reports a baseline LQRE model of rebellion, which includes only local food-related indicators, precipitation and nighttime light levels, and fixed effects by year. This model is followed by a full specification that includes all the regressors discussed above. The regression estimates in Tables 1 and 2 provide strong support for the expectations derived from the theoretical model. One issue with standard errors in strategic-statistical models is that the use of a choice-based sample might introduce bias, while the assumption of independence across within-group observations is violated (Carter, 2010). To account for these potential heterogeneities and other issues, I use bootstrapping undertaken based on 1,000 draws, clustering the standard errors for each regression stage by the actor whose utilities are captured in this stage. This takes into account the plausible possibility that errors are heterogeneous between different grid-cells and years for the same actors. Each table includes three columns. The first column corresponds to the effect of relevant indicators on the probability that the rebel will attack given food support to state forces (or their utility from attacking $U_r(AF)$). The second column reports relevant variables' effects on the probability state forces will protect a given cell-year during an attack, accounting for food support levels (or their utility from defending given an attack $U_b(AF)$). The fourth column reports the effect of relevant indicators on the decision of the rebels to not attack (or their gains from adhering to the status quo, $U_r(SQ)$).

Table 1: Determinants of Attacks and Defenses, 1998-2008 – Baseline Specification

	Attack Given Food Support $U_r(AF)$	**Defend Given Food Support** $U_b(AF)$	**Not Attack** $U_r(SQ)$
Cropland	3.495***	–	–
	(0.301)		
Wheat Productivity	–	0.184***	–
		(0.051)	
Nighttime Light[1]	2.203***	-0.141***	–
	(0.194)	(0.082)	
Precipitation[1]	2.034***	0.300***	–
	(0.231)	(0.076)	
Conflict Frequency (Lag)	–	–	-0.277***
			(0.025)
GDP Per Capita (Lag)[1]	–	–	0.304***
			(0.036)
Polity2 (Lag)	–	–	0.100***
			(0.006)
Constant	-15.14***	-1.486***	2.441
	(3.211)	(0.523)	(1.498)

Number of observations: 68,283
Akaike Information Criterion: 26,904.47
* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.
Values in parentheses are standard errors clustered by player and bootstrapped using 1,000 iterations.
$U_b(A\neg F)$ is the reference node and was normalized to zero. Fixed effects by year were included in each utility equation, although not reported here.
[1] Natural log

In line with expectation E1, the coefficient of *Cropland* is positive and statistically significant, meaning that the rebels' probability of attacking significantly increases in areas with more staple cropland. These results hold even with the inclusion of relevant controls for climatic effects and the different conditions discussed previously, the coefficient of which also follow theoretical expectations. The coefficients of *Population* and *GCP* are positive and statistically significant, suggesting that – as expected – the probability of rebel attacks increases in areas where more people reside and more economic activity takes place, as higher

Table 2: Determinants of Attacks and Defenses, 1998-2008 – Full Specification

	Attack Given Food Support $U_r(AF)$	**Defend Given Food Support** $U_b(AF)$	**Not Attack** $U_r(SQ)$
Cropland	1.635***	–	–
	(0.323)		
Wheat Productivity	–	0.017***	–
		(0.003)	
Population[1]	3.027***	0.053***	–
	(0.512)	(0.008)	
GCP[1]	5.507***	0.274***	–
	(1.391)	(0.031)	
Nighttime Light[1]	-2.470***	-0.181***	–
	(0.957)	(0.024)	
Temperature	-0.601***	-0.026***	–
	(0.148)	(0.004)	
Precipitation[1]	4.176***	0.131***	–
	(0.817)	(0.019)	
Border Distance[1]	-0.351***	–	–
	(0.051)		
Capital Distance[1]	–	-0.028***	–
		(0.005)	
Conflict Frequency (Lag)	–	–	-0.196***
			(0.026)
GDP Per Capita (Lag)[1]	–	–	0.072
			(0.048)
Polity2 (Lag)	–	–	0.080***
			(0.008)
Constant	-110.18***	-0.812***	-26.37
	(36.39)	(0.229)	(18.44)

Number of observations: 63,219

Akaike Information Criterion: 21,756.95

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.

Values in parentheses are standard errors clustered by player and bootstrapped using 1000 iterations. $U_b(A\neg F)$ is the reference node and was normalized to zero. Fixed effects by year were included in each utility equation, although not reported here.

[1] Natural log

rents can be obtained in these areas. Interestingly, once these variables are added to the model, *Nighttime Light*'s coefficient changes from positive to negative and statistically significant. This change in coefficient suggests that – once opportunity for looting is accounted for – attacks are more likely in low development areas. Moving on to my climatic controls, the coefficient of *Temperature* is negative and statistically significant, while the coefficient of *Precipitation* is positive and statistically significant, suggesting that the rebels' utility from attacking increases in cooler areas and where there is more rainfall. Finally, The coefficient of *Border Distance* is negative and statistically significant, meaning that – as past research posited (e.g., Buhaug, Gates and Lujala, 2009) – rebel attacks are more likely near the border, presumably because many groups maintain bases on the other side.

Variables' impact on the rebels' choice of not attacking also follows theoretical expectations: the coefficients of *Conflict frequency (lag)* is negative and statistically significant, while the coefficients of both *GDP Per Capita (lag)* and *Polity2 (lag)* are positive, although only the latter is statistically significant. These findings suggest that the rebels will gain from the status quo where there is little history of conflict, which lessens the pressures on groups to initiate preemptive attacks to weaken their rivals as a defensive strategy; in countries with higher average income, where it is not necessary for food to be grown locally because it can be easily obtained via alternative means (e.g., refrigeration, improved transportation due to better infrastructure), and where the state has more capacity to defeat the rebels (Koren, 2018); and in countries with more political participation, which allows different groups to resolve potential conflicts in peaceful ways rather than by escalating violence.

In line with E2, the probability that the state will defend against attack significantly increases in areas and years with higher values of *Wheat Productivity*, compared with a scenario where no food support is provided. Higher yields correspond to more food support that can be allocated annually to state forces, which increases their durability, operational range, and fighting capacity (Koren, 2018). The civilians thus benefit from higher levels of food support, where these can be allocated, because they increase the probability that the state or its auxiliaries will shield the civilians from rebel violence. As was the case with the rebels' decision to attack if food support is provided to state forces, the coefficients on *Population*, *GCP*, and *Precipitation* are positive and statistically significant, while *Temperature* and *Nighttime Light*'s are negative and statistically significant. This suggests that food support will have a noticeable impact on the probability of state defense where there are more people and more economic activity to be protected, where climatic factors facilitate agricultural productivity, and where development levels are low, which – in the baseline model – might differ from the impact of development on the rebels choice to attack. Additionally, in line with past research (O'Loughlin et al., 2012), the coefficient of *Capital Distance* is negative and statistically significant, suggesting that state forces will respond to attacks when these take place closer to the center of political and economic power.

To verify the sensitivity of my findings to alternative confounders, I also estimate a number of robustness models corresponding to the full specification and reported in Tables A.4–A.9, Supplemental Appendix. These models illustrate that my findings are robust to (i) relying on maize instead of wheat to approximate state forces' levels of food support, (ii) the inclusion of additional controls for state capacity, (iii) spatial attack dependencies, (iv) the inclusion of additional geospatial factors in both the rebels' and civilians' utilities, (v) the availability of lucrative natural resources, and (vi) the strength of the state's military. Importantly, the effects identified Table 2 hold in every case.

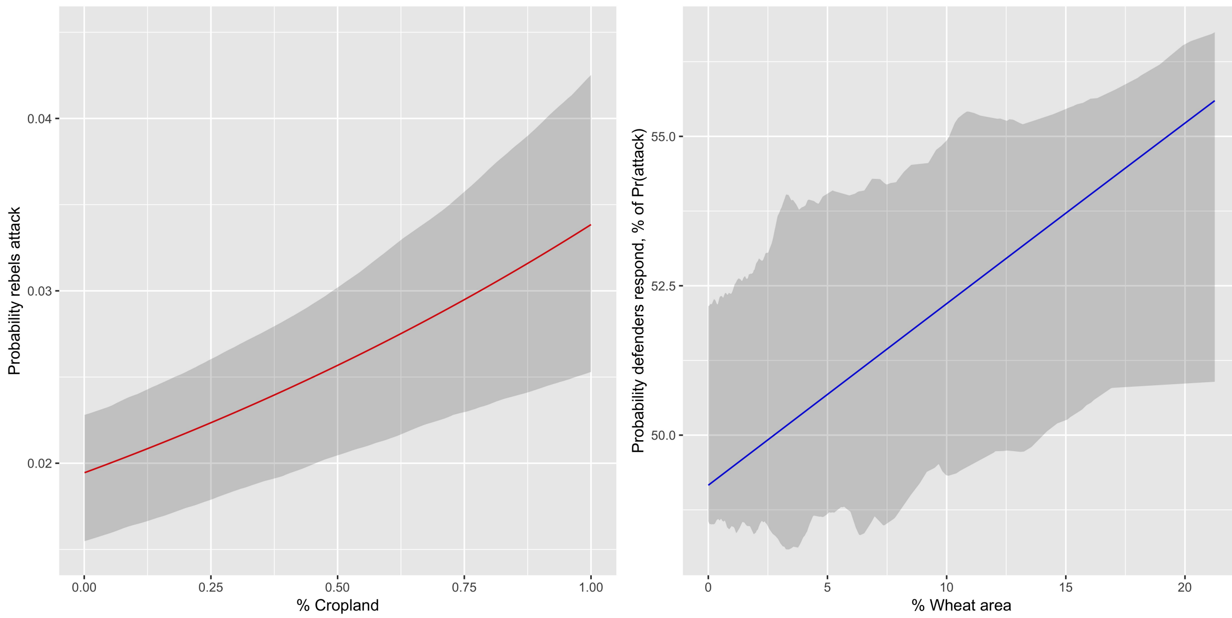
Substantive and Predictive Impact

Statistical results can provide evidence about the incentives governing the strategic behaviors of actors, but these estimates in-and-of-themselves tell us little about whether the effects identified are truly substantively meaningful in a broader context. In other words, how strong is the impact of food resources on the propensity of rebel attacks and defense responses? Are the strategic model's results generalizable to out-of-sample situations?

To verify whether these strategic interactions also have a substantive effect, I evaluate how the probability of rebel attacks varies based on potential food-support levels; and how wheat levels impact state responsiveness. To this end, Figure 3 first plots the change in the predicted probability of rebel attacks across the entire range of *Cropland*; and then the predicted probability the state will respond if attack happens (reported in percents) using the full model estimates and holding all other variables constant. The probability of a rebel attack in a given cell annually, taking into account the probabilities of both the status quo and attack without civilian food support, increases by approximately $\sim$2.5% (on average) across the range of *Cropland*. Additionally, having adjusted for the probability of rebels attacking, the probability of the state defending against an attack increases by $\sim$15% (on average) across the range of *Wheat Area* values. These quantities are relatively sizable considering the size of my grid cell year framework, the rarity of attacks in my sample (an average of 0.03 attacks per grid cell), and the fact that the interpretation of these predicted probabilities is not as straightforward as in the binary logit case due to the possibility of multiple outcomes. For comparison, despite having a statistically significant effect, the coefficient of *GCP*, a proxy of localized economic activity, have no substantive impact (i.e., an approximate $\sim$0% change) on the probability of rebel attacks in a given grid cell. These findings do suggest that the effect of food resources on preemptive rebel attacks is indeed substantive.

Given the growing importance of forecasting to the study of political violence, a valid strategic model should also possess some *predictive power*. Due to space constraints, a detailed discussion of forecasting analysis is reported in the Supplemental Appendix. More importantly, these exercises illustrate that the LQRE model improves on the standard (i.e., nonstrategic) logit in terms of prediction, which additionally confirms that accounting for the strategic behaviors of different actors with respect to food resources does indeed provide a substantive improvement in our ability to understand and forecast conflict.

Figure 3: Cropland's Effects on the Predicted Change in Probability For Attacks and Defense



Rebel Attacks State Defenses

Discussion of Scope Conditions

An important feature of this study is its reliance on data for Africa due to the different reasons discussed above. These data provide numerous advantages, namely: (i) the dyadic nature of dependent variable facilitates a direct test of the theory, (ii) Africa is the world area most susceptible to conflict as well as (iii) the effects of climate change, and where food insecurity and the necessity to live off the land are, arguably, the most prevalent (O'Loughlin et al., 2012; Koren, 2018), and (iv) the vast majority of research on the climate-food-conflict nexus focuses on Africa.

Yet, this also suggests a potential limitation, highlighted by Adams et al. (2018, 202), namely that "[s]tudies focusing on one or a few cases tend to study places where the dependent variable (violent conflict) is present and hardly relate to the independent variable." Importantly, Table A.1, Supplemental Appendix illustrates the argument, mechanisms, and findings' seem to apply to similarly agriculturally-dependent, rural societies in other world regions. However, it is important to acknowledge that more research is needed to fully verify that the present study and its conclusions is indeed applicable globally, and not just in Africa.

A second relevant scope conditions relates to violence by rebels within territories they control. While the present analysis can be reconfigured to examine when civilians are more likely to support rebels, an assumption of this study is that civilian producers of food initially side with the state, which leaves them open to attacks from rebels. However, rebels often have core areas where they can tap into civilian food production, and where they hence refrain from attacking civilians because doing so would be counter-productive (Wood, 2010; Hultman, 2009). The inclusion of *Border Distance* and *Capital Distance* in the rebels and civilians' utility functions, respectively, is designed to partially account for this issue – areas closer to the border might be more likely to be supportive of rebels and areas closer to the capital more likely to support the government (Hultman, 2009) – as are several of the robustness models reported in the Supplemental Appendix. However, because no indicators on which specific rebel group controls which cell during year t are available (to the author's knowledge), this is an issue the reader should bear in mind.

Conclusion

The use of food denial as a weapon of war is not a recent development. Throughout history and well into the 19th century, armies living off the land have been a regular characteristic of warfare, and – correspondingly – so was the preemptive destruction of food resources. By incorporating the insight that food support is crucial in facilitating military operations in these contexts and using a statistical estimator that is the structural equivalent of my theoretical argument, I confirm these expectations at the highly localized level. Indeed, once the direct effects of food support on the strategic behaviors of different actors are isolated and disaggregated, we identify a positive and substantive relationship between food productivity and localized conflict. This in contrast to analyses that do not disaggregate these strategic behaviors, which – as illustrated in Table A.10 – are less successful in terms of forecasting localized conflict, and where, if no measures to account for this strategic relationship are taken, the effect of food support might appear negative rather than positive.[15] Therefore, while these findings diverge from current conceptualizations of food and violence in some prominent studies (e.g., Miguel, Satyanath and Sergenti, 2004), they provide an explanation that can help bridge the gap between such scarcity-centric studies and research that emphasizes the role of abundance (e.g., Butler and Gates, 2012; Adano et al., 2012).

These findings also suggests ways where the framework of localized food denial attacks can be generalized to other types of resources, such as drugs and diamonds, and even political votes. As long as the incentives governing the provision and the distribution of these forms of support approximates that of food resources, the theoretical model developed here can be readily extended to reflect these additional support conceptualizations (Wood, 2010). The model can be reconfigured with relative ease to analyze when civilians are more likely to support rebels, treating state forces as the attacker. Theoretically, specific factors influencing the civilians' utility from supporting the rebels against the state can be identified. Empirically, the dependent variables can be modified to account for state attacks and rebel responses rather than the other way around, while the food support variable can be operationalized using other food resource more relevant to rebel groups, such as cattle or maize (Butler and Gates, 2012; Koren, 2018).

Finally, these findings have potential implications not only to scholars concerned with the study of political violence, but also policymakers working to ameliorate conflict and prevent renewal locally. For instance, reducing asymmetries in access to food or increasing overall food security levels within the country can reduce the need for armed groups to violently compete over these resources. Additionally, as evidenced by the effect of indicators in the status quo equation, the probability of violence can be reduced through peacebuilding exercises that emphasize development and democratization. From this perspective, the effect of improving food security can be magnified by the existence and persistence of efficient institutions that help promoting peaceful conflict resolution.

Notes

[1]I.e., "cells" of approximately 55km x 55km around the equator (Tollefsen et al., 2012). Data on staple food crops was estimated for the year 2000 (Ramankutty et al., 2008).

[2]In the Supplemental Appendix, estimates to forecast conflict on out-of-sample data for 2009-2010 to illustrate its effectiveness compared with a standard (non-strategic) model.

[3]Due to space constraints, additional background discussion is provided in the Supplemental Appendix.

[4]While the focus here is on interactions related to food support and food denial, recent studies also show that similar preemptive dynamics can cause state repression (Danneman and Ritter, 2014) and territorial disputes (Carter, 2010).

[5]In the theory developed here, *how* food resources are provided and whether they are obtained using coercion or enticement is irrelevant. Because it revolves around the strategic incentive of and the sequential moves of different actors, the model is agnostic with respect to apportionment dynamics as highlighted by, e.g., Wood (2010).

[6]Note that F stands for food support and A for attack. As discussed below, the scenario when the state decision to defend from a rebel attack but the civilians do not provide support was normalized to zero.

[7]ACLED also covers some Middle Eastern and Asian states, but only starting 2010 (and in some cases much later), whereas the controls used in some of the models forced me to constrict my temporal range to the 1998-2008 period.

[8]Note that this can affect the applicability of my findings across the entire globe (Adams et al., 2018), as discussed in more detail in Discussion of Scope Conditions.

[9]In line with theoretical expectations, rebels are defined as actors "who seek the replacement of the central government, or the establishment of a new state" or as " armed agents supported by political elites of various types, seeking to influence political processes but not change the government" or as "groups engaged in local political competition, often traditionally based contests between ethnic, community or local religious groups" and coded as such in the "actor1" category of the dataset (Raleigh and Dowd, 2015, 16-17).

[10]I.e., as having initiated events *not* coded by ACLED Version 6 as: "Headquarters or base established" or "Non-violent activity by a conflict actor" or "Riots/Protests" or "Non-violent transfer of territory" or "Strategic development" (Raleigh and Dowd, 2015).

[11]That is included in conflict interactions in ACLED where the actor1 was rebels as defined above.

[12]Importantly, as Table A.4, Supplemental Appendix illustrates, the results remain unchanged when a maize-based indicator is used instead of wheat.

[13]Note that no information on crops was available for cells located in the Sahara desert. These cells are hence dropped from analysis, reducing the probability that food support's effect is zero-inflation generated.

[14]Also it is important to note that extremely high and low luminosities might cause censoring problem with nighttime light emission data (Bluhm and Krause, 2018).

[15]See Table A.11, Supplemental Appendix.

References

Adams, Courtland, Tobias Ide, Jon Barnett and Adrien Detges. 2018. "Sampling bias in climate–conflict research." *Nature Climate Change* 8(3):200.

Adano, Wario R, Ton Dietz, Karen Witsenburg and Fred Zaal. 2012. "Climate change, violent conflict and local institutions in Kenya's drylands." *Journal of Peace Research* 49(1):65–80.

Asfaw Negassa et al. 2013. "The Potential for Wheat Production in Africa: Analysis of Biophysical Suitability and Economic Profitability." Policy paper, International Food Policy Research Institute, July 2013, `http://repository.cimmyt.org/xmlui/bitstream/handle/10883/4015/97365.pdf?sequence=1&isAllowed=y`.

Barrett, Christopher B. 2010. "Measuring Food Insecurity." *Science* 327:825–828.

Bluhm, Richard and Melanie Krause. 2018. "Top Lights: Bright cities and their contribution to economic development." UNU?MERIT Working Paper Series 2018-041.

Buhaug, Halvard, Scott Gates and Päivi Lujala. 2009. "Geography, Rebel Capability, and the Duration of Civil Conflict." *Journal of Conflict Resolution* 53(4):544–569.

Burke, M., E. Miguel, S. Satyanath, J. Dykema and D. Lobell. 2009. "Warming Increases the Risk of War in Africa." *PNAS* 106:20670–20674.

Butler, Christopher K and Scott Gates. 2012. "African range wars: Climate, conflict, and property rights." *Journal of Peace Research* 49(1):23–34.

Carter, David B. 2010. "The Strategy of Territorial Conflict." *American Journal of Political Science* 54(5):969–987.

Danneman, Nathan and Emily Hencken Ritter. 2014. "Contagious rebellion and preemptive repression." *Journal of Conflict Resolution* 58(2):254–279.

Downes, Alexander B. 2008. *Targeting Civilians in War*. Ithaca: Cornell University Press.

Fjelde, Hanne. 2015. "Farming or fighting? Agricultural price shocks and civil war in Africa." *World Development* 67:525–534.

Gleditsch, Kristian Skrede. 2002. "Expanded trade and GDP data." *Journal of Conflict Resolution* 46(5):712–724.

Hendrix, Cullen S. and Hen-Jan Brinkman. 2013. "Food Security and Conflict Dynamics." *Stability: Internatioal Journal of Security and Development* 2(2).

Hoffman, Danny. 2007. "The meaning of a militia: Understanding the civil defence forces of Sierra Leone." *African Affairs* 106(425):639–662.

Hultman, Lisa. 2009. "The Power to Hurt in Civil War: The Strategic Aim of RENAMO Violence." *Journal of Southern African Studies* 35(4):821–834.

Keller, Edmond J. 1992. "Drought, War, and the Politics of Famine in Ethiopia and Eritrea." *The Journal of Modern African Studies* 30(4):609–624.

Koren, Ore. 2018. "Food Abundance and Violent Conflict in Africa." *American Journal of Agricultural Economics* 100(4):981–1006.

Koren, Ore and Anoop Sarbahi. 2018. "State Capacity, Insurgency and Civil War: A Disaggregated Analysis." *International Studies Quarterly* 62(2):274–288.

Marshall, M. G., T. R. Jaggers and K. Gurr. 2013. "Polity iv project: Political regime characteristics and transitions, 1800-2012." Technical Report.

McGuirk, Eoin and Marshall Burke. 2017. "The economic origins of conflict in Africa." NBER Working Paper No. 23056.
URL: *http://www.nber.org/papers/w23056*

Miguel, Edward, Shanker Satyanath and Ernest Sergenti. 2004. "Economic Shocks and Civil Conflict: An Instrumental Variables Approach." *Journal of Political Economy* 112(2):725–753.

Mkutu, Kennedy. 2001. "Pastoralism and conflict in the Horn of Africa." Africa Peace Forum/Saferworld/University of Bradford.

Mowle, Thomas S. 2006. "Iraq's militia problem." *Survival* 48(3):41–58.

Nordhaus, William D. 2006. "Geography and macroeconomics: New data and new findings." *Proceedings of the National Academy of Sciences* 103(10):3150–3517.

O'Loughlin, John, Frank D. W. Witmer, Andrew M. Linke, Arlene Laing, Andrew Gettelman, and Jimy Dudhia. 2012. "Climate variability and conflict risk in East Africa, 1990-2009." *Proceedings of the National Academy of Science* 109(45):18344–18349.

Raleigh, Clionadh, Andrew Linke, Haavard Hegre and Joakim Karlsen. 2010. "Introducing ACLED: An Armed Conflict Location and Event Dataset." *Journal of Peace Research* 47(5):651–660.

Raleigh, Clionadh and Caitriona Dowd. 2015. "Armed Conflict Location and Event Data Project (ACLED) Codebook 2-15." `http://www.acleddata.com/about-acled/`.

Ramankutty, N, AT Evan, C Monfreda and JA Foley. 2008. "Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000." *Global Biogeochem. Cycles* 22:Article N. GB1003.

Ray, Deepak K., Navin Ramankutty, Nathaniel D. Mueller, Paul C. West and Jonathan A. Foley. 2012. "Recent patterns of crop yield growth, stagnation, and collapse." *Nature Communications* 3:Article N. 1293.

Signorino, Curtis S. 1999. "Strategic Interaction and the Statistical Analysis of International Conflict." *American Political Science Review* 93(3):279–297.

Sundar, Nandini. 2007. *Subalterns and Sovereigns: An Anthropological History of Bastar (1854-2006), 2nd Edition*. Delhi: Oxford University Press.

Tollefsen, Andreas Forø, Håvard Strand and Halvard Buhaug. 2012. "PRIO-GRID: A Unified Spatial Data Structure." *Journal of Peace Research* 49(2):363–374.

Von Uexkull, Nina, Mihai Croicu, Hanne Fjelde and Halvard Buhaug. 2016. "Civil conflict sensitivity to growing-season drought." *Proceedings of the National Academy of Sciences* pp. 12391–12396.

Walker, C.F. 1999. *Smoldering Ashes: Cuzco and the Creation of Republican Peru*. Durham: Duke University Press.

Weidmann, Nils B. 2013. "The higher the better? The limits of analytical resolution in conflict event datasets." *Cooperation and Conflict* 48(4):567–576.

Wood, Reed M. 2010. "Rebel Capability and Strategic Violence." *Journal of Peace Research* 47(5):601–614.