Supporting Information For

“Food Resources and Strategic Conflict”

Contents

This appendix proceeds in six parts. The first part provides and additional background discussion with some anecdotal evidence showing that preemptive conflict over food occurs worldwide. In the second part, I discuss in detail how data for coding the variables *Cropland*, *Wheat Productivity*, and *Maize Productivity* were created and validated. In the third part, different summary statistics and summary figures, mentioned but not reported in the main article, are provided. The fourth section reports a set of sensitivity analyses intended to illustrate the main analysis' findings robustness to different potential confounders. The fifth part reports forecasting exercises using out-of-sample data. In the sixth section, the estimates of the two standard (i.e., not strategic) logit models used in the forecasting exercises are reported.

Added Background Discussion

Examples that 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), are available worldwide. For instance, in Sierra Leone, troops of the Revolutionary United Front (RUF) rebel group burned and destroyed villages not only to secure food resources for their own consumption, but also to strategically hurt the government and prevent its troops from accessing these important resources (Keen, 2005). Similarly, in the Horn of Africa, where land owners – backed by governments, which have far superior military capacity – appropriated much of the traditional herding space of pastroalists, livestock raiding is frequently used to humiliate and weaken the state (Mkutu, 2001). Indeed, although analyzing every incidence where rebels attacked specific regions to deny food resources from pro-state forces is beyond the scope of this paper, a partial evaluation of more recent evidence – presented in Table A.1 below – shows that such attacks occur relatively frequently during civil war.[1]

The amount of food required to support troops varies based on unit size and type; as discussed below, well-supported militaries might need more food, but they also have the advantage of being able to mobilize food contributions from other regions, while militias and CDFs are heavily embedded in local social networks, so that even a small amount of food provision can facilitate great improvements in fighting capacity (Hoffman, 2007). Nevertheless, in each case, the importance of local food support to the state's war efforts creates strong incentives for the rebels to preemptively target areas where more food is grown, because doing so would substantially weaken pro-state forces, who require these resources to improve their own chances of victory. Attacking food abundant areas can have other beneficial externalities for the rebels such as pushing the civilians to withdraw their support from the regime, and depriving the state of tax revenue, which closely corresponds to agricultural productivity in many developing rural area (Wood, 2010; Fjelde, 2015). The amount of the civilians' land used to grow food is observable by all actors, which allows the rebels to estimate how much food is available in the region (e.g., in open stockpiles, granaries, and cattle pens), but the rebels cannot know in advance how much food the civilians will provide to pro-state forces.

Table A.1: A Partial List of Preemptive Rebel Attacks over Food Support, 1991–2008

Country	Target	Attacker	Resource	Source
Angola	civilian farmers, gov. troops	UNITA rebels	crops	Macrae and Zwi (1992)
DRC (eastern)	Tutsi farmers	Hutu and other rebels	crops, livestock	Vlassenroot and Raeymaekers (2008)
East Timor	civilians	rebel militias	livestock	The New Zealand Herald (2002)
Ethiopia	farmers	rebels, ethnic militias	livestock	Mkutu (2001)
India (Bastar)	CDF	Naxalite rebels	crops	Sundar (2007)
Kenya	farmers	Pokot/Turkana rebels	livestock	Greiner (2013)
Mozambique	civilians, gov. troops	RENAMO	crops	Hultman (2009)
Peru (Tacuna and Arequipa)	CDF	Túpac Amaru rebels	crops, livestock	Walker (1999)
Sierra Leone	military/CDF	RUF	crops	Keen (2005)
Somalia (Somaliland)	civilians	pro-Barre rebels	crops, livestock	Ahmed and Green (1999)
Sudan	civilians	Opposition forces	crops, food aid	Teodosijević (2003, 18)
Thailand (Songkhla)	farmers, civil defense forces	BRN-C rebels	crops	The Nation (2004)

Note: CDF – Civil Defense Forces

While I do not discuss this explicitly in the paper, note that this conceptualization is in line with the notion of a commitment problem. Commitment problems arise when two actors know that they will prefer to renege on their agreement in the future, meaning that even a mutually beneficial agreement cannot be struck at present (e.g., Fearon, 1995). In the context discussed here, because the civilians decide their levels of food independently of the rebels' decision whether to attack their village or not, neither side has a strong enough incentive to commit to finding a peaceful solution in advance. Preemptive rebel attacks are about *regulating the supply of food available to the state*. Note that this is not (necessarily) the same as "scorched earth" tactics, which involve the complete destruction of all means of production in a given area, whether the rebels conquer the region or not. Scorched earth tactics are one extreme type of preemptive attack, but they are neither the only one nor the most prevalent.

Data used for Constructing *Cropland*, *Wheat Productivity*, and *Maize Productivity*

Data for constructing the continuous *Cropland* indicator were obtained from Ramankutty et al. (2008), while data for constructing *Wheat Productivity* and *Maize Productivity* were obtained from Ray et al. (2012), which improve on Ramankutty et al. (2008) (as discussed below). Data on all three indicators were measured at the highly localized, $\sim$0.08$\circ$ grid level, or approximately 9km x 9km at the equator (Ray et al., 2012; Ramankutty et al., 2008).[2]

First, Ramankutty et al. (2008) created a global cropland map for year 2000. They had two sources of data: (a) Two different global satellite-based land cover data merged together (specifically, BU-MODIS and GLC2000); and (b) National and subnational census data on cropland area. The authors used regression to train the satellite land cover data against the census data, and then map cropland areas at 5 min resolution (0.08 degrees). In a second step, they further adjusted maps (scale up or down all pixels within an administrative unit) to exactly match their census data. Using this approach, Ramankutty et al. (2008) where able to capture true variations in *nutritious staple crops*, whereas the satellite based measures they built on (and which were used by past research) are less successful at distinguishing grassland and other "green" areas more broadly from staple cropland, specifically. This detailed, high-resolution information on the localized distribution of staple crops for the year 2000 were used in constructing *Cropland*, where the 0.08$\circ$ level data were averaged to the 0.5$\circ$ grid cell level.

Monfreda, Ramankutty and Foley (2008) then used the cropland map developed by Ramankutty et al. (2008) as a spatial reference to disaggregate not only area, but also yield data within each administrative unit to the 0.08 degree level for the same year (2000). They used crop yield census data by country, province, or district (depending on availability), although the authors relied on the former, and used the latter (province and district level data) only to ensure that country level data were accurate. As the compliers explain, "We chose to use the subnational data only if the total was between 50% and 200% of the FAOSTAT's national total. Otherwise, we simply used the reported national figures from FAOSTAT" (Monfreda, Ramankutty and Foley, 2008, 9). Most often, sub-national data were used to ensure that the models assigning grown hectares of each crop to each pixel were accurate, but considering the computational challenges and data collection issues with local census data, sub-national data served as a complement rather than a substitute for national level FAO data (see Figure 3 on pg. 10, Monfreda et al. 2008, for a conceptual scheme of this process).

Next, building on Monfreda, Ramankutty and Foley (2008), Ray et al. (2012) collected a large number of crop area and yield data sets from 1961 to today at sub-national and national levels, and used the cropland map by Ramankutty et al. (2008) described above as a spatial reference to disaggregate this area and yield data within each administrative unit. Note that in Ray et al. (2012), the authors only report the administrative level data, not the spatial disaggregation. The data used in this article are the row area data used in Ray et al. (2012). As mentioned in the main article, these wheat (and also maize productivity) data measure the total harvested area within a 0.08 degree cell and are expressed in hectares.[3] The grid of staple crop areas was created "by disaggregating the yield from the smallest political unit with available data in the agricultural inventory by distributing the inventory data for each administrative unit uniformly to each pixel [i.e., 0.08 $\circ$ grid] within that administrative unit" (Monfreda, Ramankutty and Foley, 2008, 10), and repeating this process annually over the entire period (Ray et al., 2012, Supplementary Information, 11-12). The crop area in each 0.08$\circ$ grid of the final map was set to zero when no reference to a crop existed in the inventory data. Information on these missing points was then interpolated from the latest five years if at higher administrative units crops reports were present (Ray et al., 2012, Supplementary Information, 12). Finally, to ensure that these local maize are data correspond to my 0.5 degree grid cell year unit of analysis, I aggregated the 0.08 pixel level data to the same 0.5 $\circ$ annual grid level. This was done by summing the total grown hectares within a given 0.08 $\circ$ pixel for all pixels within each 0.5 $\circ$ grid cell for each year in the data wherever such information was available.

Summary Statistics

Summary Tables

Table A.2: Summary Statistics of All Variables Used in Analysis, 1998-2008

	Minimum	Median	Mean	Max	SD
Attacks	0	0	0.033	1	0.179
Defenses	0	0	0.016	1	0.127
Cropland	0	0.021	0.085	1	0.154
Wheat Productivity	0	0.001	0.181	21.25	1.028
Population[1]	0	9.721	9.369	16.268	2.263
GCP[1]	0	0.076	0.271	4.455	0.490
Nighttime Light[1]	0	0	0.132	4.080	0.398
Temperature	3.625	24.683	24.397	32.617	3.764
Precipitation[1]	4.220	6.145	5.975	8.417	1.018
Border Distance[1]	0	4.913	4.682	7.574	1.137
Capital Distance[1]	1.609	6.319	6.228	7.818	0.795
Conflict Frequency (Lag)	0	0	0.316	506	3.890
GDP Per Capita (Lag)[1]	5.298	7.289	7.333	8.221	0.956
Polity2 (Lag)	-9	-1	-0.025	10	5.129
Maize Productivity	0	0.083	0.475	20.87	1.040
Attacks (spl.)	0	0	0.060	1	0.237
Mountains	0	0	0.123	1	0.243
Travel Time[1]	0	6.127	6.187	8.722	0.855
Cell Area[1]	0.141	7.996	7.869	8.039	0.612
Oil production[1]	0	13.592	9.170	18.690	8.075
Gas production[1]	0	0	1.663	7.192	2.396
Military Expenditure (Lag)[1]	0	12.612	12.525	15.350	1.649

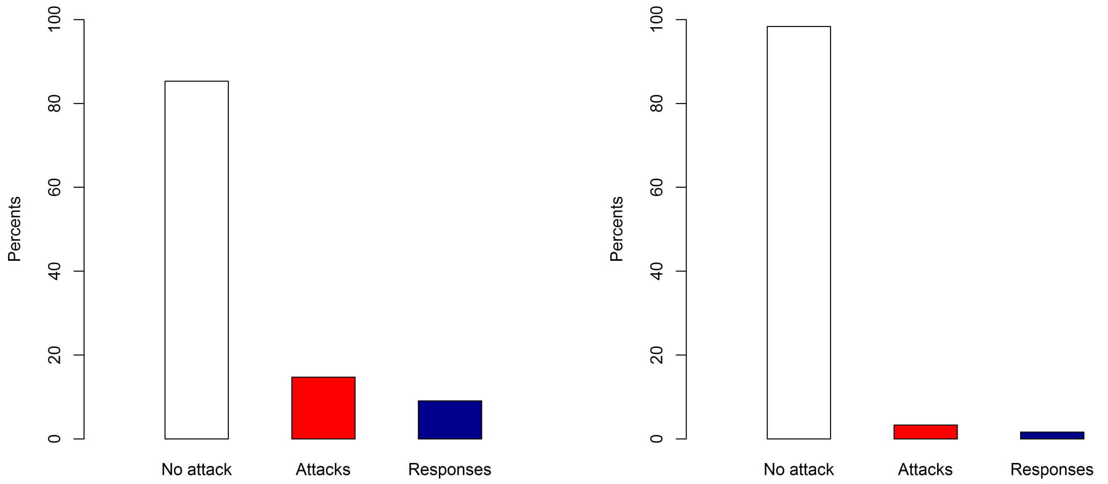
[1] Natural log

Table A.3: Summary Statistics of All Variables Used in Analysis, 2009-2010

	Minimum	Median	Mean	Max	SD
Attacks	0	0	0.044	1	0.205
Responses	0	0	0.020	1	0.140
Cropland	0	0.028	0.092	1	0.155
Wheat Productivity	0	0.002	0.181	17.11	0.881
Population[1]	0	9.854	9.489	16.27	2.281
GCP[1]	0	0.110	0.358	4.455	0.597
Nighttime Light[1]	0	0	0.207	4.104	0.498
Temperature	5.114	24.508	24.188	39.53	4.526
Precipitation[1]	0.349	6.332	5.840	7.838	1.456
Border Distance[1]	0	4.941	4.729	7.587	1.114
Capital Distance[1]	1.309	6.327	6.228	7.817	0.787
Conflict Frequency (Lag)	0	0	0.402	432	4.955
GDP Per Capita (Lag)[1]	5.513	7.596	7.669	9.925	1.007
Polity2 (Lag)	-9	2	1.917	10	5.212

[1] Natural log

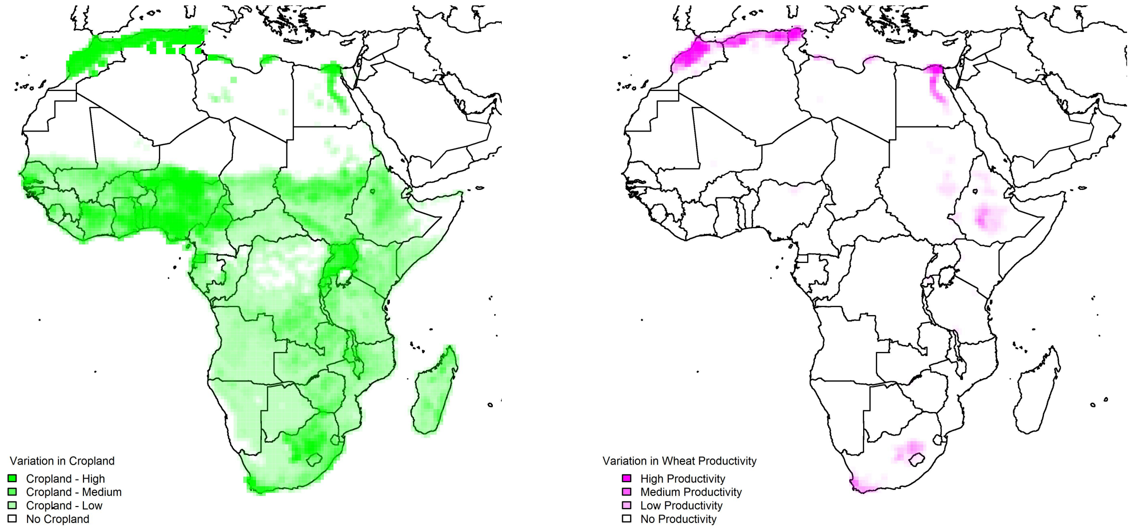
Figure A.1: The Distribution of Rebel Attacks and State Force Response by Grid Cell and Cell-Year, 1998-2008



Distribution by Grid Cell

Distribution by Cell-Year

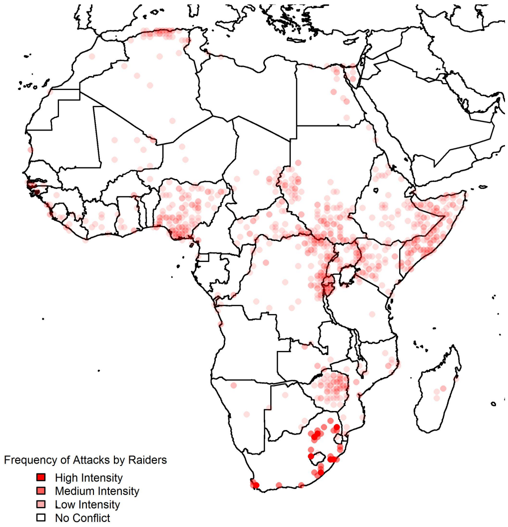
Figure A.2: The Regional Distribution of Staple Cropland and Wheat Productivity, 1998-2008



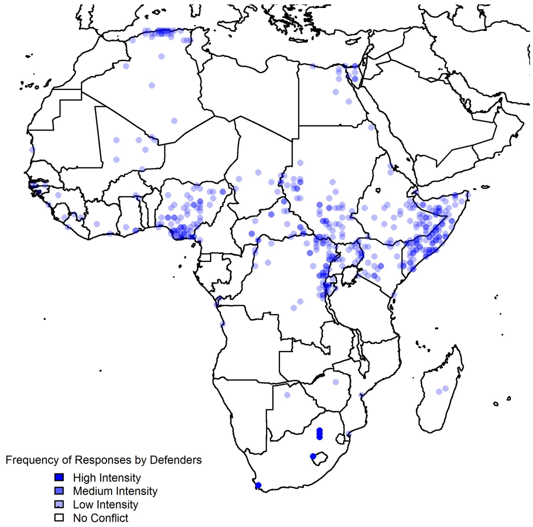
Cropland, 1998-2008

Wheat Productivity, 1998-2008

Figure A.3: The Regional Distribution of Rebel Attacks And State Force Responses By 0.5 ∘ Grids 2009-2010

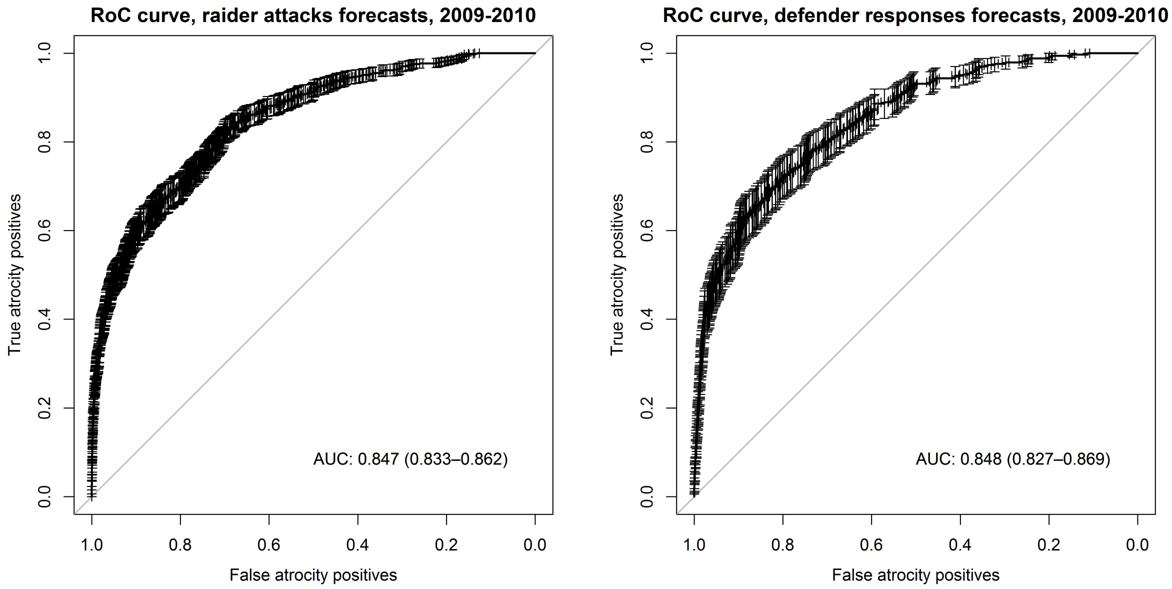


Rebel Attacks, 2009-2010



State Responses, 2009-2010

Figure A.4: ROC Curves for Each Stage in The Statistical Strategic Model



Out-of-Sample ROC:
Rebel Attacks, 2009-2010

Out-of-Sample ROC:
State Responses, 2009-2010

Note: The AUCs for each phase are $\approx 95\%$ for rebel attacks and $\approx 98\%$ of state force responses when the threshold is dichotomized at 0.5, as used by numerous studies that employ ROCs.

Robustness Analysis

This robustness section includes six alternative replications of the full analysis to test its sensitivity to alternative mechanisms and specification choices. First, to illustrate that wheat – a highly valuable crop and hence the staple expected the strongest effects of state forces responsiveness – is not driving the results, Table A.4 replicated the main model using a variable measuring maize productivity instead of wheat. As was discussed above, date for coding the variable *Maize Productivity* was created using similar methods to, and was aggregated by the author to the 0.5$\circ$ grid level in the same fashion as, the *Wheat Productivity* variable.

Second, the effect of state capacity on the decisions of the rebels to attack or follow the status quo is taken more throughly into account in Table A.5. Here a variable denoting the percent of a given grid cell that is covered by mountainous area, *Mountains* (Tollefsen et al., 2012), is included in the rebels utility from attacking when the civilians provide food support. Next, the possibility that the probability or rebel attacks increases due to attacks in neighboring cells (which lower the costs of attacking this particular region), is more throughly taken into account in Table A.6. Here, a variable denoting whether a given rebel attack took place in first order neighboring grid cells during the same year is added to the rebels' decision to attack equation.

Fourth, the effect of geospatial factors on the probability of rebel attacks and state defenses is more thoroughly taken into account in Table A.7. Here, the variables *Border Distance* and *Capital Distance* are included in both the rebels' attack and state defense during food support equations, in addition to the a variable denoting the distance from a given grid cell to the nearest city with 50,000 or more inhabitants and a variable denoting a given cell's area to account for each cell's distance from the equator, *Travel Time* and *Cell Area*, respectively (both obtained from Tollefsen et al., 2012). Fifth, considering that numerous studies have highlighted the possibility that lucrative natural resources will impact the probability of conflict (e.g., Collier and Hoeffler, 1998), Table A.8 includes country-level proxies of oil and gas production – both obtained from Ross (2011) – in the rebels' decision to attack given food support.

Finally, the effect of stronger state militaries on the rebels' decision to attack is taken more throughly into account in Table A.9. Here, a given African state's military expenditure during a given year – obtained from the Correlates of War project (Singer, Bremer and Stucky, 1972) – is included in the rebels' decision to adhere to the status quo equation. Crucially, the positive and statistically significant effect of *Cropland* on the rebel's decision to attack a given region if food is produced there, and of local food productivity – approximated using both the *Wheat Productivity* and *Maize Productivity* variables – on the probability of state defense, holds in all these alternative robustness models, which additionally confirms the argument developed in the main article.

Table A.4: Determinants of Attacks and Defenses, 1998-2008 – Maize Productivity

	Attack Given Food Support $U_r(AF)$	**Defend Given Food Support** $U_b(AF)$	**Not Attack** $U_r(SQ)$
Cropland	1.121***	–	–
	(0.317)		
Maize Productivity	–	0.009***	–
		(0.002)	
Population[1]	3.169***	0.061***	–
	(0.585)	(0.009)	
GCP[1]	4.926***	0.319***	–
	(1.617)	(0.041)	
Nighttime Light[1]	-2.371**	-0.299***	–
	(1.052)	(0.030)	
Temperature	-0.477***	-0.024***	–
	(0.156)	(0.004)	
Precipitation[1]	4.541***	0.159***	–
	(0.911)	(0.023)	
Border Distance[1]	-0.392***	–	–
	(0.051)		
Capital Distance[1]	–	-0.032***	–
		(0.007)	
Conflict Frequency (Lag)	–	–	-0.181***
			(0.026)
GDP Per Capita (Lag)[1]	–	–	0.066
			(0.049)
Polity2 (Lag)	–	–	0.069***
			(0.007)
Constant	-111.23**	-1.139***	-23.21
	(43.88)	(0.249)	(21.36)

Number of observations: 63,219
Akaike Information Criterion: 21,789.83
* 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

Table A.5: Determinants of Attacks and Defenses, 1998-2008 – State Capacity

	Attack Given Food Support $U_r(AF)$	**Defend Given Food Support** $U_b(AF)$	**Not Attack** $U_r(SQ)$
Cropland	1.802***	–	–
	(0.286)		
Wheat Productivity	–	0.015***	–
		(0.004)	
Population[1]	3.267***	0.057***	–
	(0.632)	(0.007)	
GCP[1]	5.547***	0.259***	–
	(1.781)	(0.038)	
Nighttime Light[1]	-2.430**	-0.165***	–
	(1.092)	(0.026)	
Temperature	-0.444***	-0.021***	–
	(0.160)	(0.004)	
Precipitation[1]	4.099***	0.109***	–
	(0.749)	(0.020)	
Border Distance[1]	-0.239***	–	–
	(0.047)		
Mountains	2.885***	–	–
	(0.214)		
Capital Distance[1]	–	-0.023***	–
		(0.006)	
Conflict Frequency (Lag)	–	–	-0.179***
			(0.022)
GDP Per Capita (Lag)[1]	–	–	0.091**
			(0.044)
Polity2 (Lag)	–	–	0.075***
			(0.007)
Constant	-127.80**	-0.849***	-31.64
	(55.87)	(0.272)	(29.05)

Number of observations: 62,566
Akaike Information Criterion: 21,363.44
* 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

Table A.6: Determinants of Attacks and Defenses, 1998-2008 – Spatial Attacks

	Attack Given Food Support $U_r(AF)$	**Defend Given Food Support** $U_b(AF)$	**Not Attack** $U_r(SQ)$
Cropland	0.795*	–	–
	(0.360)		
Wheat Productivity	–	0.060***	–
		(0.022)	
Attacks (spl.)	6.003***	–	–
	(0.179)		
Population[1]	0.640*	-0.080**	–
	(0.360)	(0.035)	
GCP[1]	-0.642	-0.111	–
	(1.294)	(0.077)	
Nighttime Light[1]	1.060*	-0.032	–
	(0.605)	(0.064)	
Temperature	-0.085	-0.019*	–
	(0.105)	(0.010)	
Precipitation[1]	0.803	0.098	–
	(0.549)	(0.072)	
Border Distance[1]	-0.311***	–	–
	(0.054)		
Capital Distance[1]	–	-0.095**	–
		(0.040)	
Conflict Frequency (Lag)	–	–	-0.089***
			(0.014)
GDP Per Capita (Lag)[1]	–	–	0.166***
			(0.058)
Polity2 (Lag)	–	–	0.064***
			(0.009)
Constant	-12.22	1.658**	2.707
	(11.73)	(0.701)	(8.494)

Number of observations: 63,164
Akaike Information Criterion: 19,901.01
* 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

Table A.7: Determinants of Attacks and Defenses, 1998-2008 – Geospatial

	Attack Given Food Support $U_r(AF)$	**Defend Given Food Support** $U_b(AF)$	**Not Attack** $U_r(SQ)$
Cropland	1.842***	–	–
	(0.332)		
Wheat Productivity	–	0.013***	–
		(0.003)	
Population[1]	3.099***	0.052***	–
	(0.761)	(0.008)	
GCP[1]	4.485**	0.204***	–
	(1.719)	(0.032)	
Nighttime Light[1]	-2.887**	-0.178***	–
	(1.418)	(0.025)	
Temperature	-0.553**	-0.018***	–
	(0.237)	(0.003)	
Precipitation[1]	4.952***	0.139***	–
	(1.338)	(0.022)	
Border Distance[1]	0.231	0.021***	–
	(0.547)	(0.008)	
Capital Distance[1]	-2.277**	-0.108***	–
	(1.099)	(0.017)	
Travel Time[1]	1.144	0.058***	–
	(1.165)	(0.017)	
Cell Area[1]	-17.17***	-1.030***	–
	(6.365)	(0.014)	
Conflict Frequency (Lag)	–	–	-0.180***
			(0.025)
GDP Per Capita (Lag)[1]	–	–	-0.023
			(0.048)
Polity2 (Lag)	–	–	0.069***
			(0.008)
Constant	7.966	7.349***	-34.75***
	(39.91)	(1.027)	(27.51)

Number of observations: 63,219
Akaike Information Criterion: 21,636.62
* 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

Table A.8: Determinants of Attacks and Defenses, 1998-2008 – Lucrative Natural Resources

	Attack Given Food Support $U_r(AF)$	**Defend Given Food Support** $U_b(AF)$	**Not Attack** $U_r(SQ)$
Cropland	1.426***	–	–
	(0.314)		
Wheat Productivity	–	0.013***	–
		(0.003)	
Population[1]	3.433***	0.054***	–
	(0.518)	(0.007)	
GCP[1]	5.995***	0.265***	–
	(1.419)	(0.030)	
Nighttime Light[1]	-3.037***	0.164***	–
	(0.990)	(0.022)	
Temperature	-0.714***	-0.024***	–
	(0.154)	(0.003)	
Precipitation[1]	4.515***	0.119***	–
	(0.779)	(0.017)	
Border Distance[1]	-0.368***	–	–
	(0.051)		
Capital Distance[1]	–	-0.019***	–
		(0.004)	
Oil production[1]	0.029**	–	–
	(0.011)		
Gas production[1]	0.061	–	–
	(0.044)		
Conflict Frequency (Lag)	–	–	-0.196***
			(0.026)
GDP Per Capita (Lag)[1]	–	–	0.946**
			(0.048)
Polity2 (Lag)	–	–	0.078***
			(0.008)
Constant	-131.51***	0.853***	-34.49*
	(39.72)	(0.223)	(20.83)

Number of observations: 63,219
Akaike Information Criterion: 21,745.57
* 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

Table A.9: Determinants of Attacks and Defenses, 1998-2008 – Military Expenditure

	Attack Given Food Support $U_r(AF)$	**Defend Given Food Support** $U_b(AF)$	**Not Attack** $U_r(SQ)$
Cropland	1.478***	–	–
	(0.291)		
Wheat Productivity	–	0.013***	–
		(0.003)	
Population[1]	3.732***	0.062***	–
	(0.620)	(0.008)	
GCP[1]	6.018***	0.268***	–
	(1.607)	(0.041)	
Nighttime Light[1]	-3.164***	-0.166***	–
	(1.039)	(0.028)	
Temperature	-0.757***	-0.026***	–
	(0.184)	(0.004)	
Precipitation[1]	4.537***	0.109***	–
	(0.821)	(0.019)	
Border Distance[1]	-0.447***	–	–
	(0.042)		
Capital Distance[1]	–	-0.012***	–
		(0.004)	
Conflict Frequency (Lag)	–	–	-0.179***
			(0.021)
GDP Per Capita (Lag)[1]	–	–	0.131***
			(0.041)
Polity2 (Lag)	–	–	0.069***
			(0.007)
Military Expenditure (Lag)[1]	–	–	-0.234***
			(0.026)
Constant	-136.86**	-0.877***	-33.39
	(58.67)	(0.292)	(31.32)

Number of observations: 62,528
Akaike Information Criterion: 21,257.77
* 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

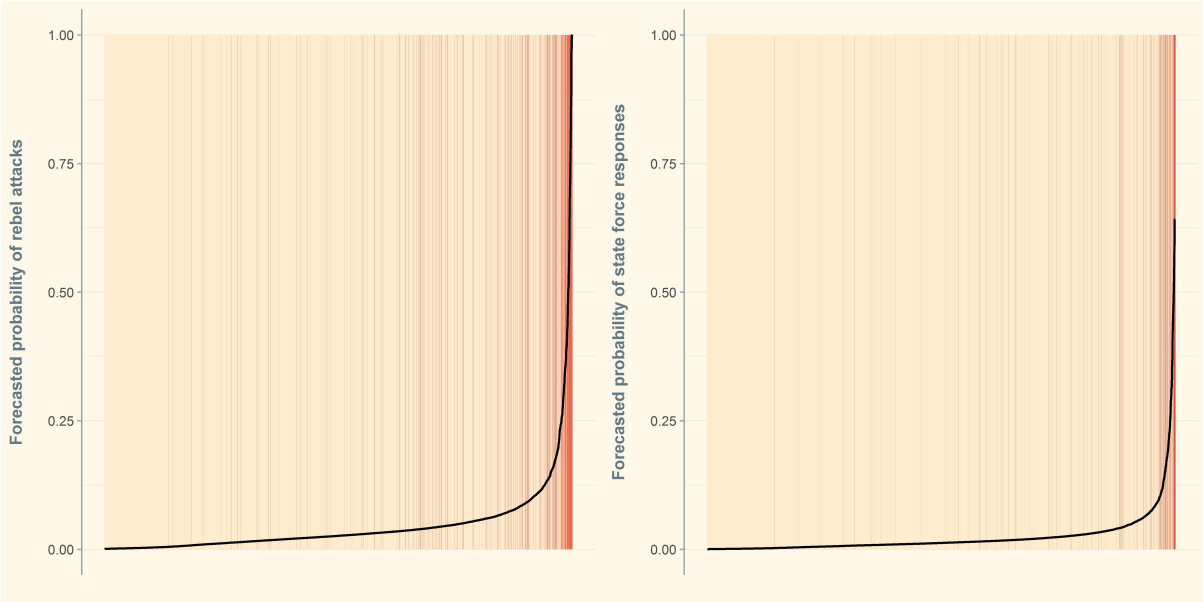
Forecasting Exercises

As mentioned in the main article, given the growing importance of forecasting to the study of political violence, a valid strategic model should also possess some *predictive power* that makes it preferred to a "coin-flip" model (i.e., a model that has a completely random chance of predicting a given conflict event). I thus evaluate the forecasting strength of the estimates derived from my strategic model for 1998-2008 on out-of-sample data for 2009-2010 in two steps. The frequencies of rebel attacks and state responses for 2009-2010 are shown in Figure A.3, and the summary statistics on the variables used in this analysis are reported in Table A.3 above.

To evaluate the forecasting strength of the estimates derived from my strategic model for 1998-2008 on out-of-sample data for 2009-2010, I report two separation plots in Figure A.5 illustrating the strategic model's ability to forecast rebel attacks and state force responses, respectively.[4] These plots evaluate the model's predictive fit by showing the extent to which the actual instances of events (dark colors in these graphs) are concentrated on the right side of the plot, while instances of no-events (light colors) are concentrated on the left side. The values on the x-axis are the model's predicted probabilities for each out-of-sample observation, and the black curve in each plot corresponds to the model's ROC with respect to each dependent variable of interest. In a model that perfectly predicts each observation, all dark colors will be concentrated on the right (Greenhill, Ward and Sacks, 2011).

As these plots show, the strategic model does a reasonably good job of predicting conflict given that most of the events are clustered on the right-hand side of the graph. Indeed, the ROC curves for this model (reported in Figure A.4, Supplemental Appendix) show that it correctly predicts approximately 85% of rebel attacks (with a 95% confidence interval of 83% $\Leftrightarrow$ 86%) and 85% of state force responses (with a 95% confidence interval of 83% $\Leftrightarrow$ 87%) for the years 2009-2010. These quantities can be compared to the forecasting strength of a completely random "coin flip" model, which should correctly predict 50% of all conflict observations.

Figure A.5: The Forecasting Accuracy of the Statistical-Strategic Model on Out-of-Sample Data, 2009-2010



Accuracy: Rebel Attacks

Accuracy: State Force Responses

Second, as shown in Table A.10, the statistical-strategic model provides a significantly better predictive fit to the data based on DeLong, DeLong and Clarke-Pearson (1988) test compared with standard logit models that do not account for the *strategic* nature of food denial conflicts (i.e., that simply include all the regressors in one equation), both when in- and out-of-sample data are concerned. In both cases, the strategic model improves prediction by about 2% with respect to both rebel attacks and state force responses compared with the standard (i.e., nonstrategic) logit, which is substantial considering, again, the size of my sample. These findings thus suggest that taking into account the strategic behaviors of different actors with respect to food resources does indeed provide a substantive improvement in our ability to forecast conflict.

Table A.10: Comparison of Prediction Strength, LQRM and Logit Models, 1998-2008

	In Sample (1998-2008)				**Out-of-Sample (2009-2010)**			
	Rebel Attacks		**State Responses**		**Rebel Attacks**		**State Responses**	
	LQRM	Logit	LQRM	Logit	LQRM	Logit	LQRM	Logit
AUC	0.82	0.80	0.83	0.81	0.85	0.83	0.85	0.83
DeLong et al. test	$z = 8.244$***		$z = 6.696$***		$z = 5.354$***		$z = 4.415$***	
Favors:	LQRM		LQRM		LQRM		LQRM	
N	63,219				15,071			

Note: * indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Null hypothesis for Delong et al.'s Test for two correlated ROC curves: true difference in AUC's is equal to zero.

Standard Logit Model Estimates

Table A.11: Logit Model Estimates of Rebel Attacks and State Force Responses, 1998-2008

	Probability of Rebel Attack	**Probability of State Response**
Cropland	0.242** (0.118)	
Wheat Productivity	–	−0.127*** (0.028)
Population[1]	0.517*** (0.024)	0.580*** (0.033)
GCP[1]	−0.116* (0.065)	0.029 (0.080)
Nighttime Light[1]	0.471*** (0.052)	0.355*** (0.066)
Temperature	0.008 (0.006)	0.012 (0.008)
Precipitation[1]	0.369*** (0.042)	0.398*** (0.056)
Border Distance[1]	−0.150*** (0.018)	–
Capital Distance[1]	–	0.231*** (0.036)
Conflict Frequency (Lag)	0.133*** (0.006)	0.077*** (0.004)
GDP Per Capita (Lag)[1]	−0.140*** (0.032)	−0.035 (0.044)
Polity2 (Lag)	−0.047*** (0.005)	−0.096*** (0.007)
Constant	−10.093*** (0.563)	−14.403*** (0.840)
Observations	63,219	63,219
Akaike Inf. Crit.	18,312.41	11,477.60

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.
Coefficient values are reported with standard errors in parentheses.
Fixed effects by year were included in each regression, although not reported here.
[1] Natural log

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