Food Policy 115 (2023) 102404

Contents lists available at ScienceDirect

Food Policy

journal homepage: www.elsevier.com/locate/foodpol

The effects of crime and violence on food insecurity and consumption in Nigeria[☆]

Heidi Kaila[a,*], Abul Azad[b]

[a] Poverty Global Practice, World Bank, 1818 H Street NW, Washington DC, USA
[b] Development Data Group, World Bank, Rome, Italy

ARTICLE INFO

Keywords:
Conflict
Victimization
Food insecurity
Consumption
Assistance
Nigeria

ABSTRACT

Households living in conflict-affected areas are vulnerable to violence and crime perpetrated by various types of actors. By exploiting variation in the timing, intensity, and spatial distribution of attacks against households in Nigeria, this study finds that becoming a victim leads to higher food insecurity and decreased food and non-food consumption. Property crimes are more detrimental to consumption and food insecurity than violence is. The findings remain robust to accounting for conflict in the geographical proximity to the household. Our results indicate that information on victimization can be used for building safety nets in conflict-affected areas.

1. Introduction and motivation

Up to two-thirds of the world's extreme poor are estimated to be living under fragility and conflict by 2030 (Corral et al., 2020). To solve the food insecurity issues of tomorrow, understanding of the relationship between food insecurity and conflict is crucial.

Households in conflict-affected areas can experience many types of violence and crime. In addition to being attacked by the main actors of the conflict, such as militants or insurgents, households are more vulnerable to criminal activity as a consequence of weakened law enforcement. While research shows that armed conflict has severe consequences for households (Blattman and Miguel, 2010; Verwimp et al., 2019), less is known about how households directly become victims of crime and violence in conflict situations. Furthermore, the implications of victimization on food insecurity remain understudied due to lack of longitudinal data on attacks against households.

In this paper, we present microeconomic evidence on the effects of victimization on household food insecurity and consumption. Using up to six rounds of panel data over a span of seven years before, during, and after a large increase in conflict in Nigeria, we exploit the variation in the timing, intensity and location of attacks against households to analyze the effects of victimization on household food insecurity and consumption. Since collecting face-to-face interviews in fragile areas can be unsafe both to the enumerators and respondents, information on the attacks was collected over the phone. Our study is unique in that we can differentiate between the extensive and intensive margins of victimization using detailed data on the attacks. Furthermore, we can differentiate between physical violence and property crime, as well as between attacks by different perpetrators.

Existing studies on victimization document the effects of attacks on households on child nutrition (Minoiu and Shemyakina, 2012, 2014), and on household economic outcomes (Rockmore, 2016). Our study contributes to this literature by shedding light on the near-term impacts on household welfare. Our panel data structure allows us to employ household fixed effects to control for time-invariant household characteristics. Our results thus shed light on the mechanisms underlying the broader literature that documents a relationship between civil conflict and child nutrition (Bundervoet et al., 2009; Akresh et al., 2011, 2012; Verwimp, 2012; Minoiu and Shemyakina, 2012, 2014).

We find that victimization leads to over 10 per cent decrease in consumption per capita at the extensive margin, similar in magnitude to Rockmore (2016). We also find that one additional attack leads to a 3–4 percent decrease in consumption per capita with both food and

☆ We thank Belinda Archibong, Chris Barrett, Christopher Boone, Emily Crawford, Brian Dillon, Victoria EsquivelKorsiak, John Hoddinott, Clement Joubert, Vasco Molini, Nadia F. Piffaretti, Carlos Rodríguez-Castelán, Saurabh Singhal, Smriti Sharma, and participants at the 2020 Households in Conflict Network Annual Conference, 2020 Midwest International Economic Development Conference, 2019 Center for the Study of African Economies conference in Oxford, and seminar participants at Cornell University and the University of Newcastle for their valuable comments. We thank Kevin Robert McGee, Michael Wild, Aibek Baibagysh Uulu and Federika Alfani for assistance with the data. Kaila gratefully acknowledges financial support from Danmarks Frie Forskningsfond (DFF) grant number: 7024-00030B. Support from Korea Trust Fund (KTF) for Economic and Peace Building Transitions is gratefully acknowledged.

* Correspondence to:
E-mail address: hkaila@worldbank.org (H. Kaila).

https://doi.org/10.1016/j.foodpol.2023.102404
Received 25 August 2021; Received in revised form 25 December 2022; Accepted 3 January 2023
Available online 17 January 2023

nonfood consumption being affected. Poor households are more likely to stay poor after becoming victimized, whereas non-poor households manage to prevent themselves from falling into poverty.

We also study food insecurity as it captures a more volatile measure of household economic well-being. We find a strong and robust positive effect of victimization on food insecurity: one attack alone can push a household from low to medium food insecurity. While the evidence on conflict and household food insecurity remains mixed (Mercier et al., 2020; Brück et al., 2019b; Dabalen and Paul, 2014; D'Souza and Jolliffe, 2013) our finding is in line with evidence from Nigeria using regional conflict measures (George et al., 2019).[1]

Another contribution of our study is to distinguish between the effects of different types of victimization to understand how different types of attacks (physical violence or property crime) and perpetrators (criminals, insurgents or actors in communal clashes) affect welfare. While a lawless situation may give rise to both politically and economically motivated attacks against households, the consequences of these attacks may be different depending on the objective and motivation of the perpetrators. Insurgents typically justify their acts by political or religious motivations towards a larger societal goal. Communal violence, on the one hand, often arises from disagreements about the distribution of resources within a community; it might also be fueled by ethnic, religious, or political arguments. Finally, crimes committed in conflict-affected areas might be motivated by purely personal economic gains. On the other hand, it is possible that given that different actors face similar constraints to maximizing the expected utility of their acts, the consequences of their acts may also be similar. Whether the consequences of crimes perpetrated by different actors differ is thus an empirical question that we examine.

Nigeria provides a suitable context to study the effects of different types of victimization due to the various ongoing conflicts. Nigeria is the largest economy and the most populous country in Africa, and has seen a sharp rise in violent conflict during the last decade. Although the Boko Haram insurgency has gained vast attention from international media, the long-standing militant and criminal activity in the oil-producing south and the increased tensions between herders and farmers also pose important threats to national security.

We find that attacks on property, such as theft or the destruction of assets, are more detrimental to food insecurity and consumption than physical violence is. We find that livestock losses are an important mechanism, which could be a direct result of livestock theft, or an indirect result, if productive assets are sold as a coping mechanism. Physical violence can directly affect the capability of adult household members to provide for one's household if a member of productive age is injured or killed. However, estimates on property crime are statistically more significant than estimates on violence. The effects also vary by perpetrator such that insurgent attacks are most detrimental to consumption, and both insurgent and criminal attacks increase food insecurity. We do not find similar results for the victims of communal clashes, that is, events related to the farmer–herder conflict.

We run several robustness checks to assess the validity of our findings. Our results are robust to a large number of both household specific as well as geographical time-varying controls, and to selecting control variables using LASSO machine learning techniques (Belloni et al., 2013). We also show that our results are robust to including conflict-related fatalities in the geographic proximity of the household in our models. Given that our model is a differences-in-differences framework, we test for parallel trends by conducting placebo tests, which we find to hold.

This paper also highlights the importance of data collection in fragile areas. Since collecting face-to-face survey data can be difficult for respondents if they are perceived to be providing information to the government, we focused on telephone surveys. The victimization data was collected over the phone from a sample of households that were part of a panel study collected between 2010 and 2016.[2] Information on outcome variables and household characteristics before, during, and after the conflict comes from the panel study. We have complemented these data with annual telephone survey data on the recall of victimization dating back to 2010. Collecting data over the phone was considered a strong alternative to face-to-face interviews because close to 90 percent of all households in the study regions had phones.

The paper proceeds as follows: Section 2 presents literature on victimization, and Section 3 discusses the evolution of conflict in the study region. Section 4 presents the data, and Section 5 presents the empirical framework. Section 6 presents the results. Finally Section 7 discusses policy implications and Section 8 concludes.

2. Literature on victimization

While the literature on the consequences of conflict on households is broad, and examines several outcomes (Verwimp et al., 2019) finding effects on schooling, poverty, child malnutrition and labor market outcomes, among others; the literature on victimization, the study on direct attacks against households in conflict situations, remains narrower.

The evidence on victimization on welfare outcomes shows negative effects: Minoiu and Shemyakina (2012, 2014) find reduced child health and nutrition outcomes in the context of the civil war in Cote d'Ivoire, with larger and statistically more significant estimated impacts when experiencing property crime than when experiencing violence. Rockmore (2016) finds in the context of Uganda, that while the experience of insecurity and as well as direct exposure to violence both reduce household consumption, the effects of direct exposure are larger.

There is also evidence on human capital and labor market effects. The seminal study by Blattman and Annan (2010) finds that abducted ex-combatants in Uganda face persistent setbacks in their human capital formation leading to reduced earnings and lower psychological well-being. In the context of Turkey, Kirbis and Nelson (2022) find that victimized individuals are more likely to become entrepreneurs, but are also highly likely to fail in business activities. In Afghanistan, Callen et al. (2014) find that fearful recollections trigger changes in risk and certainty preferences more for victimized individuals than for others, inducing a stronger preference for certainty.

Our contribution to the literature relies on distinguishing between different types of attacks against households, and by types of perpetrators, akin to recent work on victimization and political participation by Douarin et al. (2021) and heterogeneous effects on risk preferences depending on the type of conflict exposure by Rockmore et al. (2017). Given that these heterogeneous effects observed in this nascent literature on the types of victimization, and on perpetrator identities, more research can be done to understand the consequences of different types of conflict exposure.

3. Conflict in Nigeria

With more than 180 million inhabitants, Nigeria is the most populous country and the largest economy in Africa. Ethnicity and religion have played a role in the history of conflict in Nigeria at least since independence.[3]

[1] For a comprehensive review on food insecurity and conflict, see Martin-Shields and Stojetz (2019).

[2] The panel study is the General Household Survey of Nigeria (the GHS). It is part of the Living Standards Measurement Study, or LSMS, data set by the World Bank.

[3] The Biafran war between 1967 and 1970 was particularly cruel, resulting in an unprecedented humanitarian crisis.

Since the transition from military to civilian rule in 1999, violence in different regions has taken various forms. The north has experienced high levels of religious and ethnoreligious violence. The North Central region has experience a recent rise in clashes between farmers and herders. The Niger Delta region has experienced a local insurgency that has mutated into criminality and maritime piracy (Nwankpa, 2014; Marc et al., 2015).

Since 2010, the three geopolitical regions that have been most affected by conflict are the North East, the North Central, and the South South. These regions have all seen an increase in conflict levels since 2010. In the North East, conflict is largely attributable to Boko Haram. The violent radicalization of Boko Haram members and the resulting military operations have affected nearly 15 million people since 2009. Boko Haram's tactics have included multiple modes of attack, including suicide bombings, the seizure and destruction of entire villages, the destruction of basic services, forced displacement, abductions, sexual violence, and forced recruitment.

Since the start of the insurgency in 2009 until 2018, an estimated 20,000 people were killed. Nearly 2.1 million people fled their homes during the height of the conflict, of which 1.7 million remained displaced in 2018, a vast majority of them being internally displaced within Nigeria (IOM, 2018). An estimated 200,000 people were estimated to reside in neighboring countries in 2017 (OCHA, 2018). Our data indicate that 49 percent of households in the North East had experienced victimization between 2010 and spring 2017. The perpetrator was most often reported to be an insurgent (in 72 percent of the cases). Hence, Boko Haram activity was clearly felt by a large fraction of households.

The herder–farmer conflict in the North Central region centers around agricultural households and nomadic cattle-herding groups who come into conflict over land and water access. Since 2013, communal clashes between these two groups have increased. Farmland has been destroyed and forcefully occupied, livestock stolen, and crops damaged. The conflict has intensified as many northern herdsmen have moved their herding routes towards the south. There have been multiple push factors in the north: the Boko Haram insurgency, the growth of human settlements, and the degradation of pastures due to droughts. The death toll has been increasing, with 2500 fatalities recorded in 2016 alone (ICG, 2017).

Our data indicate that 25 percent of households in the North Central region experienced at least one attack between 2010 and 2017. The most common perpetrators of the events are pastoralists or nomads (45 percent), followed by insurgents (21 percent).[4] This indicates that the Boko Haram has been active in the North Central region as well, but to a lesser degree than in the North East.

In the Niger Delta – the South South region – several militant groups, targeting primarily the oil industry, have caused disruptions to the oil-led economy. The conflict has long historical roots; some form of violent conflict has been ongoing since independence. Most recently, the conflict has been related to demands for a more equitable redistribution of oil resources as well as concerns related to environmental degradation. In 2009, amnesty was declared to militants (Nwankpa, 2014; Ajodo-Adebanjoko, 2017), but new militant groups have emerged since, and fatalities have increased. In the Niger Delta region, 22 percent of households in our data reported at least one attack between 2010 and 2017, comparable to victimization intensity in the North Central region. Bandits and criminals were the most common type of perpetrators (42 percent of cases).

[4] The household survey data does not include nomadic households. Therefore, we only capture one side of the violence in the herder–farmer conflict — namely, the events where the perpetrator was a pastoralist and not the side where the perpetrator was a farmer.

4. Data

4.1. Data sources

We combine the General Household Survey (GHS) panel data with a telephone survey on household victimization conducted during 2017 among a subset of the GHS households. The three waves of the GHS were collected in 2010–11, 2012–13, and 2015–16. They include two visits each: a post-planting visit during fall and a post-harvest visit in the spring.[5]

The telephone survey on victimization was administered to 717 of the GHS panel households selected from the second visit of wave 3.[6] The telephone survey elicits information on whether households had become victims of violence, property-related crimes and other conflict-related incidents since 2010 based on participants' recall of the period between January 2010 and May 2017, for each calendar year.[7] The survey covered the three most conflict-affected geopolitical zones within 16 states of Nigeria.[8] Households from local government areas (LGAs) with high conflict exposure were oversampled.[9] Conflict-affected areas were oversampled to assure a decently high number of victimized households. A random sample might have resulted in an insufficient sample of victimized households, which would have restricted the scope of the analysis. Due to the oversampling, the sample drawn was not representative at the level of the geopolitical zone, as in the GHS. Indeed, there is geographical clustering of victimization: of the 717 households across 99 LGAs, victimization was concentrated in 52 LGAs — almost half (47) of the LGAs did not have any victimization.[10] Even though the conflict was widespread in these areas, the GHS panel data set contains a low fraction of households that have migrated during the data collection. All households in the telephone survey had lived in their LGA of residence during the entire time.

To account for the sampling biases, we use probability weights throughout. This renders the estimates representative at the geopolitical zone level (North East, North Central, and South South), as is the case with the GHS. The weights used were constructed using the wave 3 GHS panel weights as a benchmark, adjusting for the probability of being in the sample. The weights correct for biases from the oversampling, for nonresponse, and for the fact that a minority of the households surveyed in wave 3, visit 2, did not have a phone or did not provide a phone number. The mobile phone penetration rates are close to 90 percent in all three regions, however.[11] In Appendix E we show that the results are robust to unweighted regressions.

4.2. Descriptive statistics

Victimization has increased in all regions since 2010. Fig. 1 shows the share of household victimized in each state over the years 2010, 2012, 2014 and 2016. The peak of victimization in the North East occurred in 2014, with a decrease from 2014–16, while in the North

[5] The GHS dataset is collected by the National Bureau of Statistics of Nigeria in collaboration with the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) project by the World Bank https://www.worldbank.org/en/programs/lsms/initiatives/lsms-ISA#29.

[6] The GHS waves include between 4500 and 5000 households, the sample size of wave 3 s visit is 4579.

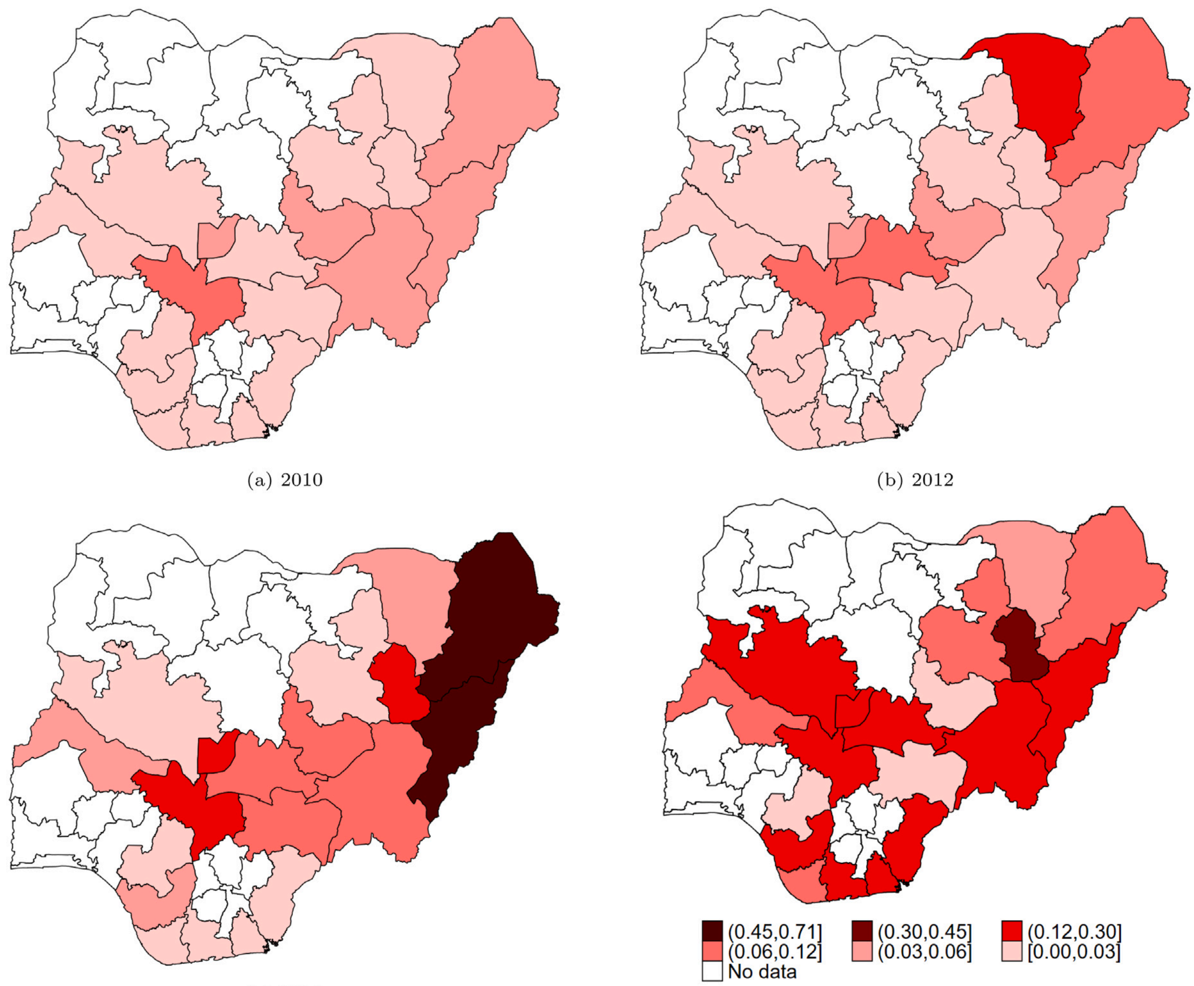
[7] Brück et al. (2015) outline survey procedures for measuring conflict exposure in LSMS surveys.

[8] The telephone survey was conducted between March and May 2017. Appendix A, Section 2, provides additional information on the survey procedures. Appendix B outlines information on how the geopolitical zones were selected.

[9] High conflict exposure was defined as more than 10 conflict events during 2012–14 recorded in the ACLED database (Raleigh et al., 2010).

[10] There is an average of 7.24 households per LGA.

[11] The mobile phone penetration rate is 84 percent in the North East, 90 percent in the North Central, and 83 percent in the South South.



(a) 2010 (b) 2012 (c) 2014 (d) 2016

Fig. 1. Victimization over time and space. *Note:* The maps show the share of households victimized in a given year.
Sources: Based on telephone survey data collected by the World Bank and the National Bureau of Statistics (NBS).

Central and South South zones victimization rates increased steadily reaching a peak in 2016. Fig. 2 shows us the evolution of attacks between 2010 and spring 2017. Fig. 2(a) displays the data of all attacks as well as property crime and violence.[12] While we separate victimization by property crimes and physical violence, our main variable of interest encompasses all types of attacks against households. Robberies and theft carry the risk of a physical altercation, and the fear associated with that risk. From 2012 onward, the level of household victimization has increased substantially.

Fig. 2(b) displays the mean number of attacks per year by the most common types of perpetrators: insurgents, bandits and criminals, and pastoralists and nomads. Attacks by insurgents peaked in 2014, the most violent year of the Boko Haram insurgency. The number of attacks involving bandits and criminals is increasing over time. The number of attacks involving pastoralists and nomads increased in 2013, and remained at that level. The decrease in 2017 is not representative of the entire year but only until May 2017. It is meaningful to study the perpetrator and the type of event separately because both violence as well as attacks on property are perpetrated by all types of perpetrators.[13]

There are potential limitations in measuring victimization. Recall bias can occur if past attacks are not remembered as well as more recent attacks. To address this issue, we compare the time distribution of victimization to the conflict intensity from the ACLED database. Figure B-1 in appendix B displays the time distribution of attacks; the vertical axis shows what fraction of all attacks between 2010 and 2016 for the data set in question happened in each specific year. This yields a meaningful comparison between our data set and the ACLED which does not suffer from recall bias, as ACLED uses newspaper reports on conflict events and fatalities. However, the qualitative differences between the datasets implies that we cannot compare the level of conflict and victimization across the data sets, which is why we compare the trends. We can see that the time trend in both conflict events and fatalities in the ACLED is

[12] The violent attacks include the killing of a household member, whether any household has suffered physical aggression (with or without a weapon), and whether any household has become injured/disabled after a direct attack. The property attack variable includes reports of any household member robbed (money or assets), household dwelling suffered from robbery, Household dwelling burned down/destroyed/seriously damaged/occupied, household land occupied/expropriated/made unproductive, and household assets intentionally destroyed/seriously damaged.

[13] Although violence is most often perpetrated by insurgents (30.5 percent of all violent attacks between 2010 and 2016), bandits and criminals and pastoralists and nomads are often reported as perpetrators of violence (18.5 percent and 22.8 percent, respectively). Similarly, whereas attacks property are most often perpetrated by pastoralists and nomads (38.7 percent), 20.5 percent and 22.3 percent of property crime is perpetrated by insurgents and bandits and criminals, respectively.

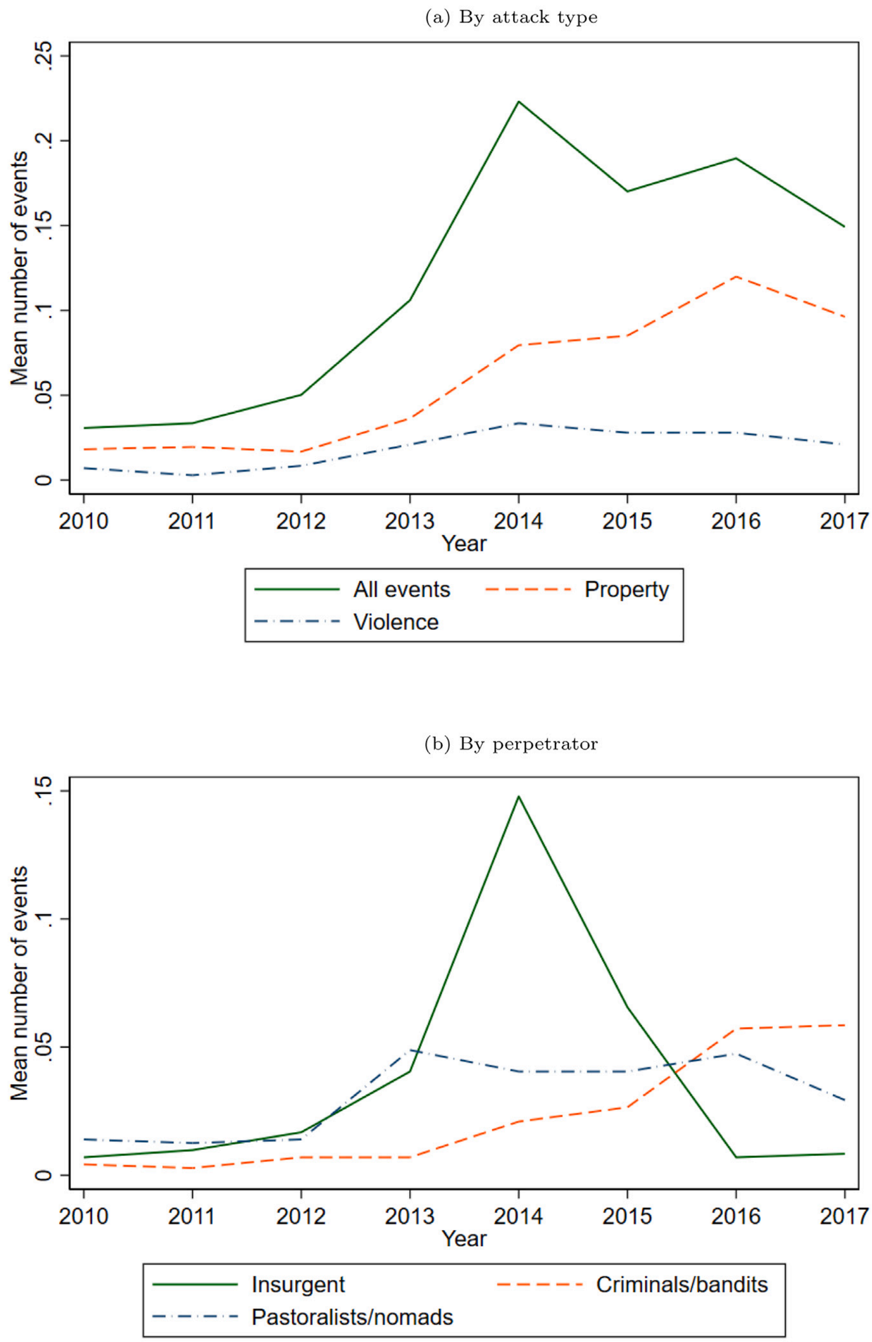


Fig. 2. Mean number of attacks per household over time. *Note:* The year 2017 only contains data until spring 2017.
Sources: Based on telephone survey data collected by the World Bank and the National Bureau of Statistics (NBS).

similar to the time trend of victimization. Although it is impossible to fully rule out recall bias, we do not consider it a major obstacle for our analysis because the conflict intensities have evolved similarly across the data sets. Any presence of recall bias, however, would bias our estimates downward.

We also compare the spatial distribution of the attacks between our data set and the ACLED over the course of 2010 to spring 2017, which was used as our basis for selecting the most appropriate geopolitical zones for the telephone survey. By comparing figures B-2a (the number of events in ACLED) and B-2b (household victimization in the telephone survey), we can see that also the geographical patterns across the geopolitical zones are similar in the two data sets.

Given that our outcomes are measured at the household level, we would ideally want to capture victimization of all household members. However, given that most of the respondents are male, events experienced by female household members might be underreported, which is supported by the fact that we have almost no reports on sexual violence (For evidence on Boko Haram on gender-based violence, see Ekhator-Mobayode et al. (2020)). We also have low reports of police or military violence; which may also be an underestimate given that the survey was administered by the government.

The data show that many attacks reported in the survey were not reported to anyone in the community, including community and

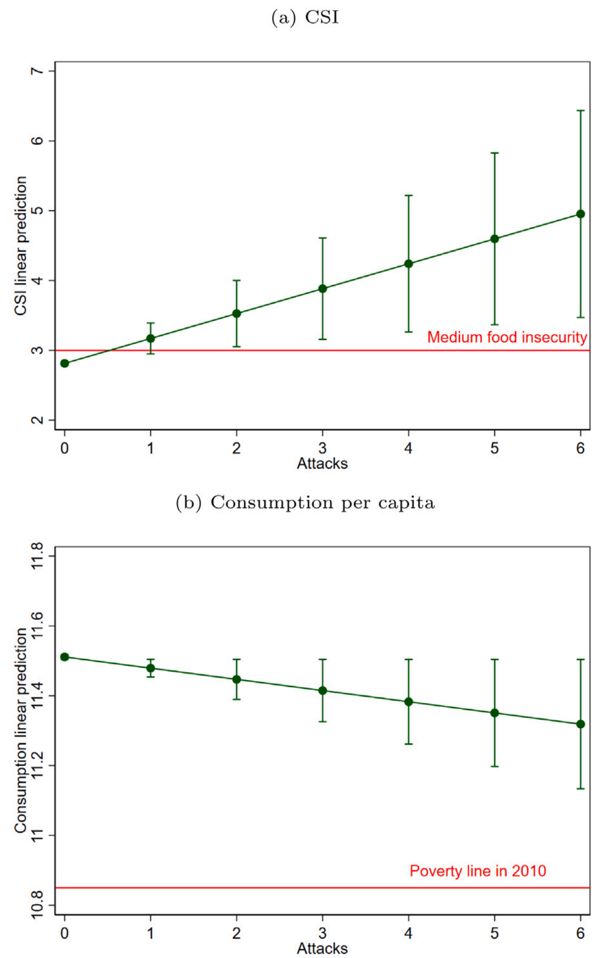


Fig. 3. Marginal effects of main outcome variables. *Note:* The medium food insecure threshold is CSI = 3. The threshold of poverty is the log of the real per capita poverty line in 2010, 51 482.14 Naira. Marginal effects are based on regressions in Tables 2 column 3, Table 5 column 3.

religious leaders as well as authorities.[14] Given that the number of attacks reported in our survey is much higher than the number reported to authorities, we believe that despite our concerns of underreporting, our respondents show trust in the enumerators. Indeed, the households were visited multiple times by the survey teams since 2010 and prior to the telephone survey, which surely helped build trust. However, in the presence of any underreporting our victimization measure and our results would be downward biased.

The evolution of the consumption levels is displayed in figure A-1a. Consumption per capita has been increasing in all three regions, but the increase is especially rapid in the South South. Poverty is derived from the consumption measure such that the poverty line is US $ 1.90 per capita per day consumption.

Food insecurity can be either transitory or chronic (World Bank, 1986). The former is associated with periods of intensified pressure caused by shocks, such as natural disasters, economic collapse, or conflict; the latter refers to problems of continuing low incomes. Food insecurity is measured using the reduced coping strategies index (henceforth CSI) by Maxwell and Caldwell (2008), and figure A-1b, shows the evolution of the CSI over time. The CSI is designed to answer the question "What do you do when you don't have enough food and don't have enough money to buy food?" The CSI measures how often during the previous seven days a household had to resort to any given coping strategy, based on the idea that the more people have to cope, the greater their food insecurity.[15] The CSI is a suitable tool to track and monitor trends in food insecurity within the same population. The index takes values from 0 to 56, with 0 denoting no food insecurity and 56 denoting extreme food insecurity. We have displayed a categorical version of the variable in order to show which fraction of the households are to some extent food insecure. During each visit, over 20 percent of households suffer either from medium or high food insecurity, with a slight increase over time.[16] The average food insecurity in the sample is 2.87, not highly food insecure (Table 1, panel b).

Summary statistics are presented in Table 1, panels a and b, for the wave-based consumption analysis and for the round-based food insecurity analysis, respectively. All summary statistics are weighted. We can see that 25 percent of the sample were poor, with the highest poverty incidence and lowest consumption per capita being in the North East, whereas the reverse holds true in the South South.[17] In any given wave, the households experienced on average 0.21 attacks per wave, with the highest incidence being in the North East and the lowest in the South South. We can see that attacks on property are more common than violence, and both of those attack types are most common in the North East.

Attacks perpetrated by insurgents are the most common in the North East (0.35 events per household per wave; see Table 1, panel a), but they also occur in the North Central. Attacks by bandits and criminals occur in each region, but they also are most prevalent in the North East. Attacks by pastoralists and nomads are most prevalent in the North Central (0.15 events per household per wave), but they occur in the two other regions as well.

We also study mental health as an additional outcome variable. We use the Center for Epidemiologic Studies Depression Scale (CES-D) available in wave 3 (Jamison et al., 2018). The 10-item scale has been shown to strongly predict clinical diagnoses of depression and anxiety disorders (Weissman et al., 1977). The score takes values from 0 to 30, higher values reflecting poor mental health, where 10 denotes a threshold level for significant depressive symptoms. The CES-D score was the highest in the North East, although the mean values are similar across regions (Table 1, panel c). Poor mental health is a strong concern as 28 percent of respondents report values exceeding the threshold of depression.[18]

Household size is largest in the North East and smallest in the South South, and the fraction of female household heads is lowest in the North East and highest in the South South. Similarly, household heads are

[14] Among victimized households, 77 percent in the North East, 34 percent in the North Central, and 26 percent in the South South had not reported the most recent attack to any authority.

[15] The questions of the CSI index, followed by the weight given to each question in parenthesis: Rely on less preferred foods (1), Borrow food or rely on help (2), Limit portion size (1), Restrict consumption by adults for children to eat (3), Reduce number of meals (1). Our module includes questions using the second version of the CSI referred to as the "reduced" CSI. The advantage of the reduced CSI relative to the original context-specific CSI is that it performs better in comparing across different context. The module has been shown to correlate just as well with other food insecurity indicators as the original index. This is important for our study, given that there are large differences across different regions in Nigeria. We use the abbreviation CSI to indicate the "reduced" CSI. The construction of the index is also explained in detail in Appendix A.

[16] For consistency, data from wave 1, visit 1, are omitted from this figure because they are omitted from the analysis.

[17] Note that although these means are weighted, they are based on a subsample of households in each of the three regions. Therefore, they do not necessarily correspond fully to the poverty incidence of each region reported in the poverty analysis done using the full GHS.

[18] See Jamison et al. (2018) for more analysis with these data.

Table 1
Summary statistics.

	Pooled		North East		North Central		South South	
	Mean	sd	Mean	sd	Mean	sd	Mean	sd
a. Wave based sample								
Consumption per capita (ln)	11.5	0.74	11.3	0.67	11.4	0.74	11.7	0.73
Poverty status	0.25	0.43	0.36	0.48	0.29	0.45	0.15	0.35
Food consumption (ln)	11.1	0.76	11.0	0.70	11.0	0.77	11.2	0.77
Non-food consumption (ln)	10.0	0.94	9.62	0.83	9.91	0.93	10.4	0.91
Health expenditures (ln)	3.42	3.57	2.54	3.21	3.68	3.55	3.75	3.72
Education expenditures (ln)	6.17	3.71	5.40	3.41	6.54	3.50	6.34	3.99
Any attack	0.076	0.26	0.15	0.35	0.073	0.26	0.032	0.18
Attacks	0.21	0.96	0.43	1.37	0.21	1.01	0.064	0.42
Attacks violence	0.035	0.27	0.058	0.31	0.029	0.32	0.025	0.19
Attacks property	0.089	0.43	0.15	0.52	0.12	0.54	0.021	0.18
Insurgents	0.10	0.68	0.35	1.27	0.026	0.28	0	0
Bandits/criminals	0.024	0.19	0.046	0.22	0.012	0.16	0.020	0.20
Pastoralists/nomads	0.056	0.54	0.015	0.18	0.15	0.90	0.0024	0.070
Asset index	0.050	0.31	−0.029	0.34	0.041	0.28	0.11	0.30
TLU (ln)	0.29	0.67	0.77	1.01	0.22	0.45	0.048	0.31
HH size	6.49	3.70	8.54	4.42	6.37	3.42	5.29	2.75
HH head male	0.84	0.36	0.95	0.21	0.88	0.33	0.74	0.44
HH head age	50.1	15.0	47.9	13.4	49.8	14.9	51.6	15.9
HH head years of education	7.34	5.65	5.98	5.57	7.32	6.11	8.21	5.10
Area of residence	0.36	0.48	0.27	0.44	0.41	0.49	0.37	0.48
Hh head monogamous	0.57	0.49	0.47	0.50	0.59	0.49	0.63	0.48
Hh head polygamous	0.21	0.41	0.45	0.50	0.22	0.42	0.059	0.23
Hh head formerly married	0.17	0.37	0.043	0.20	0.14	0.35	0.27	0.44
HH head employed	0.87	0.34	0.84	0.37	0.91	0.28	0.85	0.36
Observations	2151		516		825		784	
b. Wave-visit based sample								
Coping Strategy Index (CSI Score)	2.87	5.54	1.79	3.86	2.40	5.37	3.94	6.33
Attacks	0.13	0.69	0.26	0.97	0.13	0.74	0.039	0.32
Attacks violence	0.021	0.20	0.035	0.22	0.018	0.25	0.015	0.14
Attacks property	0.053	0.30	0.091	0.37	0.073	0.36	0.013	0.14
Insurgents	0.058	0.49	0.21	0.91	0.016	0.22	0	0
Bandits/criminals	0.014	0.14	0.028	0.16	0.0071	0.11	0.012	0.15
Pastoralists/nomads	0.034	0.39	0.0091	0.11	0.091	0.65	0.0015	0.054
HH size	6.50	3.72	8.61	4.45	6.36	3.41	5.28	2.76
HH head female	0.16	0.37	0.049	0.22	0.13	0.33	0.26	0.44
HH head age	50.3	14.9	48.0	13.1	50.2	14.7	51.9	15.9
HH head years of education	7.37	5.67	6.02	5.58	7.31	6.14	8.27	5.12
Rural	0.64	0.48	0.73	0.44	0.59	0.49	0.63	0.48
Hh head monogamous	0.57	0.50	0.47	0.50	0.59	0.49	0.62	0.49
Hh head polygamous	0.21	0.41	0.44	0.50	0.22	0.42	0.057	0.23
Hh head formerly married	0.18	0.38	0.046	0.21	0.15	0.36	0.27	0.45
HH head employed	0.87	0.34	0.84	0.37	0.91	0.28	0.84	0.36
Asset index	0.057	0.32	−0.027	0.35	0.050	0.29	0.12	0.31
Observations	3550		860		1377		1313	
c. CES-D	7.64	5.40	8.97	5.63	6.00	4.35	8.16	5.71
Observations	717		175		276		266	

Notes: Weights used in all calculations. sd = standard deviation; ln = natural logarithm; HH = household; CES-D = Center for Epidemiologic Studies Depression Scale.

least educated in the North East and most educated in the South South. Twenty-one percent of all households in the sample are polygamous, with the highest share of polygamous households in the North East and the lowest in the South South (Table 1, panels a and b). These summary statistics illustrate the differences between Nigeria's poorer north and relatively wealthier south.

5. Empirical specification

5.1. Panel data sets

We construct two panel data sets for the two outcome variables, consumption per capita and food insecurity. Figure D-1 in appendix D illustrates the timing of the measurement of the outcome variables in relation to the telephone survey on victimization.

For consumption, we have data from three waves that have two visits each; post-planting and post-harvest. The consumption aggregate is readily constructed as the median of the consumption level of those two visits, that is measured at three points in time (2010–11, 2012–13, and 2015–16) and adjusted by household size. The CSI, comprises the seven-day recall questions administered during each visit of the GHS — that is, altogether six times during the panel. For simplicity, we talk about rounds to refer to the wave-visit frequency using six points in time. Given that we are interested in the lagged victimization to alleviate concerns of reverse causality, we are dropping the CSI in 2010 from the analysis because no information on victimization exists for 2009. Figure D-2 illustrates the timing of the merge between the outcome variables and the victimization data for the wave-based and the round-based panels.

5.2. Empirical model

We run a fixed effects model of the following form

$$Y_{i,r,t,w} = \alpha_i + \beta \sum_{j=w-1}^{t-1} Attacks_{i,j} + \gamma X_{i,r,t,w} + \theta_w + \tau_{r,w} + \varepsilon_{i,r,t,w} \quad (1)$$

where $Y_{i,r,t,w}$ is either (log) consumption per capita or the CSI in household i in region r in year t and the corresponding wave (or round) w.[19] Household fixed effects capturing time-invariant household characteristics are denoted by α_i, and wave or round fixed effects as θ_w.[20] The variable $\sum_{j=w-1}^{t-1} Attacks_{i,j}$ records the number of attacks for each household i for each time period j, where j is the number of years between the previous round $w-1$ and the previous year $t-1$ (in case the last visit of the previous wave or round took place before $t-1$). Our attack measure captures the intensity of victimization as measured by the number of events the household reported in the telephone survey.

5.3. Threats to identification

While household fixed effects capture all time-invariant household characteristics, we also control for time-varying household and geographic characteristics, $X_{i,r,t,w}$. The household controls are household head gender and age, household head education in years and employment status, and dummies for different marital statuses (Table 1). We display results both with and without controls because some controls could be "bad controls", that is, directly affected by victimization. We control for geographical time-varying factors at the household level, such as temperature and precipitation, which could directly affect our outcome variables (listed in table A.1). We also control for conflict in the geographical vicinity, at the 20 km radius of the household. This is a dummy variable taking the value one for any fatal incident (using the same recall as for the household attacks) as recorded in the ACLED database. Finally, we consider that there may be regional trends that correlate with the intensity of victimization, which we account for by using region-time trends $\tau_{r,w}$ (region-wave with the wave-based panel and region-round in the round-based panel). We cluster our standard errors at the LGA level to account for spatial correlation.

Our analysis might be confounded if households receive assistance from informal safety nets after an attack. Therefore, we also remove households that reported any assistance after the most recent attack (from the telephone survey) as well as households that reported having received either cash or in-kind transfers in the GHS panel. Just 6 percent reported any assistance.

Even though the fixed effects remove the time-invariant household characteristics, we are interested in examining whether the targeting of households was systematically driven by household characteristics. We do so by investigating differences across households that were victimized and those that were not victimized by running a t-test with our outcome variables of interest and with a number of household and geographical characteristics. We find that in 2010–11, households that had become victims at any time during the survey differed little from the victimized households. The results are reported in table C-1, where Panel a compares household characteristics, and panel b household location-specific geographical characteristics.[21] Panel a shows that in the first round, there are no statistically significant differences in the poverty status, level of consumption per capita, and the CSI between households that had been victimized between 2010–17 and households that had not. There are a couple of statistically significant differences, for example, larger households and polygamous households were more likely to have been victimized. This is unsurprising because the attack variable includes several types of attacks where a single household member is the victim (such as a household member being robbed or a household member being injured). Larger households (a variable that correlates strongly with polygamy) mechanically are more likely to report such events because these households have more members. Further, at the 10 percent significance level there are also differences in the variables household head being employed and household head years of education, suggesting slightly higher employment and education among heads from non-victimized households. From panel b, we can see that the geographical characteristics of victimized and not victimized households vary in 2010–11, as we might expect given the geographical clustering of the attacks. These variables are related to exogenous conditions such as rainfall and temperature.

Additionally, we explore the conditional targeting of attacks in Table C-2 using wave 1 observable characteristics of households as well as geographical covariates as predictors of violence. Two of the geographic variables remain statistically significant, indeed suggesting geographical variation in victimization as also shown in Table C-1. None of the other coefficient estimates are statistically significant in this model.

Due to these observed differences, we cluster the standard errors at the LGA level even though our variable of interest, household victimization, varies at the household level. We also control for all geographical variables listed in table C-1, panel b.[22] We control for all household demographic characteristics in table C-1 (household size; household head gender, age, and years of education; area of residence; and dummies for marital status and employment status).

Table C-1 panel a also shows that the main outcomes of interest, household food insecurity and consumption per capita, were not ex ante correlated with victimization. Thus, even though attacks are clustered geographically, the targeting of households within a given LGA seems to be less systematic. While this is the case, it is not required for identification because household fixed effects absorb the location-specific time-invariant differences across households.

As a robustness check, we consider an alternative recall specification, where we estimate the effects of only period $t-1$ attacks on outcomes at time t. Because the data was not collected across evenly spaced time intervals, doing so makes the specification more uniform across the waves. The specification is described in Section 6.4.3, and illustrated in figure E-1.

6. Results

6.1. Food insecurity

Table 2 shows the results from estimating the effect of victimization on the CSI and its components. The index is a weighted sum of its components taking values from 0 to 56, while all of its components take values between 0 and 7, indicating the amount of days in the last week a household had resorted to a specific strategy.

We find that a additional attack leads to a 0.34–0.38 increase in the CSI (Table 2, columns 1–3). Given that a mean household has a CSI of 2.9, that is, just below the threshold level of 3 'medium food insecurity', just one attack can push the mean household from low to medium food insecurity. This is close to the average effect, as the mean household reported 0.87 attacks in total over the period 2010–17. Results are robust to adding controls (geographical and household specific, as listed in table C-1) and region-survey round fixed effects that capture region-specific time trends (Table 2, columns 2 and 3, respectively). Fig. 3(a) illustrates the marginal effects of the regression in Table 2 column 3 showing how just one attack can push the mean household over the threshold of "medium food insecurity".

[19] Since wave captures in each case a median of two measures in separate calendar years, the notation does not overlap with that of the calendar year, which is the frequency at which the attack data was collected. The correct interpretation of the notation w in relationship with the calendar year is to consider that wave 1 corresponds to the year 2011, wave 2 to 2013, and wave 3 to 2016.

[20] In the consumption analysis for the three waves, and in the food insecurity analysis for the six rounds.

[21] The summary statistics and the description of the geographical variables are presented in tables A-1 and A-2.

[22] The summary statistics of the geographical variables are presented table A-1.

Table 2
The effect of victimization on food insecurity: intensive margin.

	CSI				Rely on less preferred foods		Borrow or rely on help		Limit portion size		Restrict adult consumption		Reduce number of meals	
	(1)	(2)	(3)	(4) Assistance=0	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Attacks	0.388**	0.336**	0.346***	0.284**	0.088***	0.052*	0.007	0.013	0.065*	0.071**	0.050**	0.048**	0.069**	0.054**
	(0.150)	(0.143)	(0.120)	(0.132)	(0.026)	(0.031)	(0.012)	(0.012)	(0.034)	(0.029)	(0.024)	(0.023)	(0.035)	(0.023)
Conflict	0.485	0.568*	0.478	0.450	0.132	0.140	0.013	0.005	0.069	0.068	0.042	0.051	0.133**	0.107*
	(0.302)	(0.297)	(0.300)	(0.293)	(0.091)	(0.103)	(0.020)	(0.019)	(0.054)	(0.053)	(0.046)	(0.044)	(0.066)	(0.058)
Controls	No	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-round FE	No	No	Yes	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	3550	3468	3468	3253	3550	3468	3550	3468	3550	3468	3550	3468	3550	3468
R-Squared	0.014	0.029	0.039	0.040	0.007	0.028	0.015	0.053	0.021	0.036	0.006	0.026	0.011	0.029
Mean of dep. var.	2.869	2.857	2.857	2.849	0.926	0.921	0.092	0.091	0.507	0.506	0.262	0.262	0.468	0.462

Notes: Dependent variable is the CSI and the components of that index. The weights of the index are denoted in parenthesis: Rely on less preferred foods (1), Borrow food or rely on help (2), Limit portion size (1), Restrict consumption by adults for children to eat (3), Reduce number of meals (1). The variable "Attacks" denotes the number of attacks household has been experienced. All regressions include household fixed effects. In column 4, households that report having received assistance have been removed from the sample. Data used are from the six visits of the GHS and a telephone survey on victimization. All regressions are conducted using weights. Controls include all household and geographical variables listed in appendix table C.1. Standard errors clustered at the local government area level. Significance: *** p < 0.01; ** p < 0.05; * p < 0.1.

Table 3
The effect of victimization on food insecurity: extensive margin.

	CSI				Rely on less preferred foods		Borrow or rely on help		Limit portion size		Restrict adult consumption		Reduce number of meals	
	(1)	(2)	(3)	(4) Assistance=0	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Any attack	1.472***	1.385***	1.294***	1.035**	0.315***	0.189	0.010	0.017	0.248**	0.260***	0.205**	0.191**	0.274***	0.238***
	(0.509)	(0.522)	(0.484)	(0.499)	(0.109)	(0.123)	(0.034)	(0.035)	(0.095)	(0.091)	(0.095)	(0.093)	(0.102)	(0.083)
Conflict	0.499	0.579*	0.486	0.455	0.135	0.141	0.013	0.007	0.071	0.070	0.044	0.052	0.135**	0.107*
	(0.301)	(0.296)	(0.300)	(0.292)	(0.091)	(0.104)	(0.020)	(0.019)	(0.054)	(0.053)	(0.046)	(0.044)	(0.067)	(0.058)
Controls	No	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-round FE	No	No	Yes	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	3550	3468	3468	3253	3550	3468	3550	3468	3550	3468	3550	3468	3550	3468
R-Squared	0.015	0.030	0.040	0.040	0.007	0.028	0.015	0.053	0.022	0.036	0.007	0.026	0.012	0.030
Mean of dep. var.	2.869	2.857	2.857	2.849	0.926	0.921	0.092	0.091	0.507	0.506	0.262	0.262	0.468	0.462

Notes: Dependent variable is the CSI and the components of that index. The weights of the index are denoted in parenthesis: Rely on less preferred foods (1), Borrow food or rely on help (2), Limit portion size (1), Restrict consumption by adults for children to eat (3), Reduce number of meals (1). All regressions include household fixed effects. In column 4, households that report having received assistance have been removed from the sample. Data used are from the six visits of the GHS and telephone survey for conflict. All regressions are conducted using weights. Controls include all household and geographical variables listed in appendix table C.1. Standard errors clustered at the local government area level. Significance: *** p < 0.01; ** p < 0.05; * p < 0.1.

Some households may have received assistance from informal safety nets to overcome the consequences of attacks. In column 4 of Table 2 we removed households that reported having received any assistance after the most recent event from the sample, reducing the coefficient estimate to 0.28 units in the CSI. The result remains significant at the 5 percent level. This suggests that households that received assistance were perhaps slightly more affected by the adverse events than households that did not receive assistance.

Columns 5–14 in Table 2 show that households change their coping strategies after an attack, particularly those that reduce food consumption: limiting portion sizes, restricting adult consumption so children can eat, and reducing the number of meals. Interestingly, households do not increase their borrowing of food or their reliance on help, in line with the low level of assistance received. These variables take values from 0 to 7. We can see for instance that an additional attack increases the amount of days reducing the number of meals by 0.05. This might seem small, but given that the households are resorting to these multiple coping strategies simultaneously, the cumulative effect is captured by the CSI.

Next, we investigate the results on the extensive margin. Table 3 repeats the analysis presented in Table 2, such that the variable "Any attack" takes value 1 if household has experienced at least one event in period t and zero otherwise. We can see that victimization leads to 1.3–1.5 units increase in the CSI (columns 1–3). The coefficient estimates are over three times the magnitude of those of the intensive margin: This is consistent with the mean number of cumulative attacks experienced between 2010–17 being close to three. We find that the results when removing households who had received assistance remain similar to those on the intensive margin. Similarly, at the extensive margin we do not see an increase in borrowing or relying on help, but we do see an increase in all other coping strategies. Finally, both the significance and magnitude of the results change little when including control variables.

Note that in conflict-affected areas, conflict might affect the food insecurity of all households to some extent. These results illustrate the added effect of being attacked. Evidence suggests that in areas with active Boko Haram insurgency, food production has decreased (Adelaja and George, 2019). In these areas, markets might operate less efficiently, resulting in disruptions to food supply. Finally, net-buyer households that rely on markets as their main source of food may have experienced lower purchasing power resulting from lower income or increased food inflation, which has been documented a concern for food access (Azad and Kaila, 2018). We have therefore included the variable Conflict that captures the presence of any fatal event reported in the 20 km radius of the household (as recorded in the ACLED database) to the models. While the coefficient estimates are positive, they are statistically significant only for the 'reduce number of meals' outcome variable. This indicates that indeed attacks against households have a strong effect over and above conflict in the geographical proximity.[23]

In Table 4 we show results by event type and across perpetrators. Attacks on property include robbery of dwellings and individuals, dwelling or land being destroyed or occupied, and household assets being destroyed. Violent attacks include killings, injuries, and physical aggression.[24] It is important to note that robberies carry a risk of physical violence, even when it is not realized, and the results should be interpreted keeping this in mind.

The most commonly reported perpetrators are insurgents, bandits and criminals, and pastoralists and nomads.[25] It is possible that the same household has been exposed to different types of attacks perpetrated by different actors. In our empirical specification we therefore compare households that have experienced, for example, attacks on property (and possibly other attacks) with households that have not experienced attacks on property (but might have experienced other

[23] In Section 6.3.2 we explore the interaction effect of conflict and attacks against households further.

[24] The rest of the categories include any household member being a victim of: sexual violence, forced work, kidnapping/abduction, restricted from going to school or seeking health care, or being made a refugee or being internally displaced. Limitations to the gender perspective of the telephone survey are discussed in Azad et al. (2018).

[25] There are other perpetrators in the data, such as individuals and the military. Their frequencies, however, are so low that we do not consider these groups in our analysis. See appendix A for details on the categories and on how these questions were asked in the survey.

Table 4
The effect of victimization on food insecurity by event and perpetrator type.

	Event type				Perpetrator type					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Attacks property	0.769**	0.691***								
	(0.314)	(0.231)								
Attacks violence			0.609	0.509						
			(0.373)	(0.336)						
Insurgents					0.552***	0.462**				
					(0.160)	(0.177)				
Bandits/criminals							1.981***	1.997***		
							(0.625)	(0.585)		
Pastoralists/nomads									−0.034	0.053
									(0.071)	(0.084)
Conflict	0.494	0.488	0.502	0.509*	0.490	0.489	0.533*	0.537*	0.514*	0.518*
	(0.301)	(0.300)	(0.303)	(0.301)	(0.300)	(0.300)	(0.299)	(0.299)	(0.301)	(0.300)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-round FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	3550	3468	3550	3468	3550	3468	3550	3468	3550	3468
R-Squared	0.013	0.039	0.012	0.038	0.014	0.039	0.015	0.041	0.011	0.037
Mean of dep. var.	2.869	2.857	2.869	2.857	2.869	2.857	2.869	2.857	2.869	2.857

Notes: Dependent variable is the CSI and the components of that index. The weights of the index are denoted in parenthesis: Rely on less preferred foods (1), Borrow food or rely on help (2), Limit portion size (1), Restrict consumption by adults for children to eat (3), Reduce number of meals (1). All regressions include household fixed effects. Data used are the six visits of the GHS and a telephone survey on victimization. All regressions are conducted using weights. Controls include all household and geographical variables listed in appendix table C.1. Standard errors clustered at the local government area level. Significance: *** p < 0.01; ** p < 0.05; * p < 0.1.

Table 5
The effect of victimization on consumption per capita: intensive margin.

	Consumption (ln)				Nonfood (ln)		Food (ln)	
	(1)	(2)	(3)	(4) Assistance=0	(5)	(6)	(7)	(8)
Attacks	−0.035***	−0.046***	−0.036***	−0.031**	−0.045*	−0.046*	−0.029**	−0.031**
	(0.013)	(0.011)	(0.013)	(0.013)	(0.023)	(0.024)	(0.014)	(0.014)
Conflict	0.000	0.021	0.006	0.021	−0.041	−0.026	0.020	0.016
	(0.043)	(0.044)	(0.047)	(0.049)	(0.061)	(0.053)	(0.054)	(0.058)
Controls	No	Yes	Yes	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-round FE	No	No	Yes	Yes	No	Yes	No	Yes
N	2125	2084	2084	1953	2125	2084	2125	2084
R-Squared	0.162	0.222	0.239	0.244	0.108	0.156	0.131	0.210
Mean of dep. var.	11.499	11.502	11.502	11.487	10.012	10.014	11.071	11.075

Notes: Dependent variables are household log consumption per capita and log per capita consumption split into food and nonfood consumption. The variable "Attacks" denotes the number of attacks the household has been experienced. All regressions include household fixed effects. In column 4, households that report having received assistance have been removed from the sample. Data used are from the three waves of the GHS and a telephone survey on victimization. All regressions are conducted using weights. Controls include all household and geographical variables listed in appendix table C.1. Standard errors clustered at the local government area level. Significance: *** p < 0.01; ** p < 0.05; * p < 0.1.

attacks).[26] This allows us to compare the magnitude of different types of attacks.

In columns 1–4 in Table 4, we report the results on the most common types of attacks, property attacks and violence. Columns 5–10 show results split by the perpetrator. We can see that attacks on property lead to increased food insecurity more than violence does, by 0.7 units in the CSI. The results are strongest for bandits/criminals (an increase of 1.9 units, columns 7–8) and insurgent attacks (0.46 units, columns 5–6). The conflict variable is marginally significant in these specifications, consistent with the estimates in Tables 2 and 3.

[26] We have also run the analysis so that we are dropping from the comparison group in each regression the households that have experienced other attacks, such that the comparison is between attacks of violence and no attacks, and attacks on property no attacks, and so forth. The results are similar and are available from the authors by request.

6.2. Consumption

Table 5 shows the results for estimating the relationship between victimization and (log) consumption per capita. We can see that one additional attack decreases consumption by 3.5–4.6 percent (columns 1–3). In column 4, we removed households that reported having received assistance. We can see again that the magnitude drops slightly, to 3.1 percent. This is consistent with the food insecurity results: households that received any assistance at some point had been harder hit. Columns 5–8 in Table 5 disaggregate the results between food and nonfood consumption. Both forms of consumption are affected by victimization. Fig. 3(b) illustrates the marginal effects of the regression in Table 5 column 3. We can see that while there is a notable decrease in per capita consumption, even six attacks in a given period do not push the mean household below the poverty line. This is in line with poverty transition results in Section 6.3.1.

Table 6 repeats the analysis of Table 5 for the extensive margin. At the extensive margin victimization leads to 11 percent decrease in

Table 6
The effect of victimization on consumption per capita: extensive margin.

	Consumption (ln)				Nonfood (ln)		Food (ln)	
	(1)	(2)	(3)	(4) Assistance=0	(5)	(6)	(7)	(8)
Any attack	−0.116**	−0.146**	−0.109*	−0.098	−0.142*	−0.128	−0.110	−0.115
	(0.057)	(0.057)	(0.056)	(0.060)	(0.078)	(0.085)	(0.074)	(0.074)
Conflict	−0.001	0.018	0.003	0.019	−0.043	−0.031	0.019	0.015
	(0.043)	(0.044)	(0.047)	(0.049)	(0.060)	(0.053)	(0.054)	(0.058)
Controls	No	Yes	Yes	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-round FE	No	No	Yes	Yes	No	Yes	No	Yes
N	2125	2084	2084	1953	2125	2084	2125	2084
R-Squared	0.161	0.220	0.237	0.243	0.107	0.154	0.131	0.210
Mean of dep. var.	11.499	11.502	11.502	11.487	10.012	10.014	11.071	11.075

Notes: Dependent variables are household log consumption per capita and log per capita consumption split into food and nonfood consumption. The variable "Any event" takes value 1 if household has experienced at least one event in period t and zero otherwise. All regressions include household fixed effects. In column 4, households that report having received assistance have been removed from the sample. Data used are from the three waves of the GHS and telephone survey for conflict. All regressions are conducted using weights. Controls include all household and geographical variables listed in appendix table C.1. Standard errors clustered at the local government area level. Significance: *** p < 0.01; ** p < 0.05; * p < 0.1.

consumption per capita (column 3). As with food insecurity, also here the coefficient estimates are between three and four-fold to those of the intensive margin, albeit measured with less precision.

For reference, studies on militant and terrorist activity find similar effects: Rockmore (2016) finds a 16 percent decrease in consumption among households victimized during the militant activity of the Lord's Resistance Army (LRA) in Northern Uganda while Abadie and Gardeazabal (2003) find a 10 percent decrease in GPD per capita as a consequence of terrorist activity in the Basque country.[27] Our results build upon these studies by providing household panel data evidence combined with detailed information on attacks against households at the extensive and intensive margin. Table 7 reports the results from a model with events split by the type (columns 1–4) and the perpetrator (columns 5–10). Columns 1 and 2 show that the decrease in consumption per capita is driven by attacks on property, with a 8.7–9.2 percent decrease for an additional attack. The coefficient estimates for violence are negative, but they are not statistically significant.

In columns 5–10 we split the attacks by perpetrator. The results are strongest for the insurgent attacks leading to a decrease in consumption per capita by more than 4 percent, and the result is statistically significant at the 1 percent level. The results are slightly stronger when controls and region-survey wave fixed effects are added. Although the attacks in which the perpetrator is reported to be a bandit/criminal or a pastoralist/nomad are not statistically significant, they are of the negative sign. The result indicates a stronger effect of victimization in areas where Boko Haram has been active. The conflict variable is not statistically significant in most specifications and close to zero.

6.3. Additional results

6.3.1. Poverty transitions

Next, we investigate whether poor households are more likely to stay in poverty after having experienced attacks and, conversely, whether nonpoor households are more likely to fall to poverty after an attack. We address this question by estimating models of the following form

$$Poor_{i,l,t,w|non-poor_{i,l,t,w=1}} = \alpha + \beta \sum_{j=w-1}^{t-1} Attacks_{i,j} + \gamma X_{i,r,t,w} + \theta_w + \lambda_l + \varepsilon_{i,r,t,w} \quad (2)$$

and

$$Non-Poor_{i,l,t,w|non-poor_{i,l,t,w=1}} = \alpha + \beta \sum_{j=w-1}^{t-1} Attacks_{i,j} + \gamma X_{i,r,t,w} + \theta_w + \lambda_l + \varepsilon_{i,r,t,w} \quad (3)$$

We split the sample across the poverty status in wave one ($w = 1$). The variable $Poor_{i,l,t,w|non-poor_{i,l,t,w=1}}$ takes the value 1 if a household i in the LGA l that was non-poor in wave 1 switched to poor in either of the subsequent waves and 0 if the household stayed non-poor. Similarly, the variable $Non-Poor_{i,l,t,w|non-poor_{i,l,t,w=1}}$ takes the value 1 if a household that was poor in wave 1 became non-poor in either of the subsequent waves and 0 if it stayed poor throughout. The variable λ_l denotes LGA fixed effects, and the rest of the variables are as previously noted, also controlling for conflict in the geographic vicinity as previously. We use a linear probability model to estimate the specifications above.

The transition probabilities between being poor and non-poor are presented in table C-3. While there is persistence in staying non-poor across the waves, there is movement to both directions. For example from wave 1 to wave 3 it was more likely for a household to move from poverty to being non-poor (51.2 percent) than staying poor (48 percent). The results on poverty transitions (table C-4) show that becoming a victim is preventing a household from graduating out of poverty (columns 1–3), while it does not affect the likelihood of falling into poverty. At this threshold, both property crime and violence have statistically significant impacts. As previously, we also find that insurgent attacks are more likely preventing households from graduating out of poverty than other type of attacks. The coefficient on the conflict variable is statistically insignificant, although the same sign as the attack variables, consistent with the estimates on consumption.

6.3.2. Victimization and conflict

Next, we analyze whether the effects of victimization vary across localities that have experienced conflict related fatalities and localities that have not. We use the variable Conflict that denotes whether there were any fatalities in a 20 km radius from the surveyed cluster using data from ACLED.[28] The results are presented in tables C-5 and C-6. We can see from column 1 that the inclusion of the Conflict indicator does not change the coefficient estimates from the comparable models in column 3 in Tables 2 and 5, the coefficient estimates of victimization

[27] In contrast, Serneels and Verpoorten (2015) find that households living in high-violence localities during the Rwandan genocide in 1994 had 28 percent lower consumption levels in 2000 than households in localities with no conflict.

[28] The recall period is the same as for the victimization measures illustrated in Appendix D.

Table 7
The effect of victimization on consumption per capita by event and perpetrator type.

	Event type				Perpetrator type					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Attacks property	−0.087**	−0.092**								
	(0.038)	(0.035)								
Attacks violence			−0.024	−0.038						
			(0.033)	(0.029)						
Insurgents					−0.040**	−0.049***				
					(0.020)	(0.015)				
Bandits/criminals							−0.067	−0.051		
							(0.073)	(0.072)		
Pastoralists/nomads									−0.039	−0.028
									(0.024)	(0.020)
Conflict	0.001	0.015	−0.006	0.008	−0.003	0.012	−0.006	0.007	−0.003	0.010
	(0.044)	(0.046)	(0.043)	(0.046)	(0.043)	(0.046)	(0.043)	(0.046)	(0.043)	(0.046)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-round FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	2125	2084	2125	2084	2125	2084	2125	2084	2125	2084
R-Squared	0.162	0.236	0.158	0.233	0.161	0.236	0.159	0.233	0.159	0.233
Mean of dep. var.	11.499	11.502	11.499	11.502	11.499	11.502	11.499	11.502	11.499	11.502

Notes: Note: Dependent variables are household log consumption per capita and log per capita consumption split into food and nonfood consumption. All regressions include household fixed effects. Data used are from the three waves of the GHS and a telephone survey on victimization. All regressions are conducted using weights. Controls include all household and geographical variables listed in appendix table C.1. Standard errors clustered at the local government area level. Significance: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

are similar when conflict exposure is accounted for. Furthermore, the variable Conflict only has a weak statistically significant relationship with food insecurity, a finding in line with George et al. (2019), but not with consumption. Odd-numbered columns from column 3 show this relationship for different types of attacks and perpetrators.

We also interact the conflict indicator with victimization. Our results point to a significant interaction effect: victimization is more detrimental outside the areas that have experienced conflict, and less detrimental in areas with conflict (even numbered columns in tables C-5 and C-6). This implies that in areas with poorer security, victimization leads to a smaller decrease in consumption and a smaller increase in food insecurity. It could be that households residing close to active armed conflict had already adjusted to the lower security situation.[29] Overall, our results show that victimization has an independent effect on food insecurity and consumption per capita even when conflict in the geographical proximity is accounted for.

6.3.3. Health and education expenditures

To understand what is driving the results on the nonfood consumption expenditures, we look at two key components: health and education expenditures per capita. The results are presented in table C-7. We find that attacks overall do not have an effect on these expenditures (columns 1 and 2). Disaggregated results show, however, that when perpetrators are nomads, there is a statistically significant increase in health expenditures by 21.8 percent. Attacks on property lead to a decrease in education expenditures by as much as 39 percent. The disaggregated results show that households increase their health expenditures after certain attacks, which comes at the expense of decreased education expenditures, a heterogeneity masked in the aggregate consumption result in Table 5. The fact that insurgent attacks are not significant for these variables might be indicative of the poor situation of health care and education in regions with high Boko Haram activity. In these areas, schools and health care centers have been attacked by insurgents, which has led to lower educational attainment (Bertoni et al., 2019). While the conflict variable remains insignificant for these specifications, as for those of the total consumption per capita, the signs of the coefficients are negative.

6.3.4. Mental health

Food insecurity has been shown to be related to poor mental health, in various dimensions. Food insecurity leads to psychosocial stressors, such as uncertainty about procuring food, tension within households from inability to provide food, shame and guilt.[30] Recent research also shows that malnutrition is a mechanism leading to long-term negative mental health as a consequence of conflict (Singhal, 2019).

In table C-8 we investigate the relationship between attacks that occurred between 2010–16 and the mental health as measured by the log CES-D score in 2016. Given that we do not have a panel structure for this analysis and are therefore unable to control for time-invariant unobserved household characteristics, the results should be interpreted as exploratory. The odd-numbered columns of table C-8 present the results without controls. We find that an additional attack is related to a 4.6 percent higher CES-D score. This result is significant at the 5 percent level and is perfectly robust to adding controls. The marginal effects of column 4 are displayed in figure C-1. We can see that while being exposed to conflict increases the CES-D score, even the 6th event does not yet push the mean respondent over the threshold of depression.

Differentiating between attacks on property and violence we find that one additional violent attack is related to a 17–18 percent higher CES-D score, and this result is significant at the 1 percent level (table C-8, columns 5–6). We do not find a statistically significant relationship between property crime and mental health. Our results suggests that although violence seems to have a relatively weak effect on economic outcomes, there are consequences from violence on mental health.

[29] This result is at odds with Minoiu and Shemyakina (2012, 2014), who find that victimization in conflict-affected areas is more detrimental than elsewhere. The important difference in our definitions of victimization and conflict is that while Minoiu and Shemyakina (2014) consider victimization as acts related to the civil war, we consider all kinds of crime, perpetrated by various type of actors. Also our conflict indicator is time-varying and defined more locally, thus related to more recent eruptions of conflict at the proximity to the household.

[30] For details, see Trudell et al. (2021) for a systematic review.

6.3.5. Mechanisms

We investigate potential mechanisms that may lead households to become food insecure and reduce their consumption after an attack. We investigate whether the households lose assets as a consequence of victimization. The results are presented in Table C-9. We find that victimization leads to a reduction in a households asset holdings in the form of livestock holdings, but not durable household assets. We measure livestock holdings by constructing a variable for Tropical Livestock Units and durable assets by constructing an asset index using factor analysis.[31] Indeed, livestock is a productive asset, while not all durable assets are necessarily used in a productive manner. Losing livestock can be detrimental to consumption directly via reduced food consumption, or indirectly through losses in income generated by sales of livestock by-products. We also investigate whether victimization led to decreased productivity of crop production by creating a variable for total agricultural output (in tons) and land area for crop production.[32] While the coefficient estimate on output is negative, we do not find statistically significant evidence on either channel. The results are presented in Table C-10.

6.4. Robustness checks

6.4.1. Alternative CSI

In the main analysis, we have used the CSI with five items, a measure considered to be valid across different contexts. The GHS food insecurity module has a sixth item, "Limit the variety of foods", that can be included in the index. We have therefore conducted the analysis with an index that includes this additional item (in the construction of the index, this item takes the lowest weight, 1). The results are presented in appendix table E-1. We can see that the results are statistically significant at the one percent level, and they are similar to those in Table 2. The results on the additional item separately (columns 5 and 6) are statistically significant at the 5 percent level.

6.4.2. Using LASSO to select controls

Next, we use a machine learning technique LASSO to select the control variables in our regressions (Belloni et al., 2013). This allows us to consider a large number of potential controls, the inclusion of which would be considered overfitting if implemented in an OLS framework, as LASSO performs a model selection check based on the best predictors of out outcome variables in order to select a set of covariates that are jointly correlated with the variables of interest.[33] The results are presented in tables E-2 and E-3, and they can be considered as a robustness check for Tables 2 and 4, and 5 and 7, respectively.[34] We can see that among the 177 controls considered for the food insecurity analysis, between 14 and 33 are chosen. Similarly 6–18 controls are chosen for the consumption analysis from the 174 considered. We can see that all the results are robust to using the LASSO machine learning technique to select controls that are best predictors.

6.4.3. Alternative lag structure of conflict

In our main specification, the number of years of recall on attacks varies across waves because the outcome variables are not measured at even time intervals. This can be problematic because food insecurity and consumption are measured using the same recall period. Due to this discrepancy, we run a robustness check where the lag structure of victimization is uniform across the waves. This model takes the form

$$Y_{i,r,t,w} = \alpha_i + \beta Attacks_{i,t-1} + \gamma X_{i,r,t,w} + \theta_w + \varepsilon_{i,r,t,w} \tag{4}$$

where Attacks in $t-1$ denotes attacks occurred during the previous year of the second round of each specific wave in the case of consumption and, in the case of food insecurity, the previous calendar year. This specification has its own drawback because we are omitting the peak year of the Boko Haram insurgency (2014). The timing is illustrated in figure E-1.

Tables E-4 and E-5 present robustness checks for the results on food insecurity (Tables 2 and 4) and consumption (Tables 5 and 7), respectively. Overall, our main results remain unchanged with the alternative lag structure. The effects are even slightly stronger for food insecurity, suggesting a strong immediate effect. The effects of violence are stronger, when violence is only restricted to events in the close past. Overall, the check suggests that the effects of the attacks further in the past might be diminishing over time, perhaps indicating recovery from the initial shock.

6.4.4. Placebo checks

Future victimization should not affect current outcome variables. Therefore, we run the placebo tests on the effect on victimization in period $t+1$ on outcomes in period t. The prior is that we should not find a statistically significant relationship between these variables if parallel trend assumptions hold. Table E-6 displays these checks for Tables 2 and 4 on food insecurity, and table E-7 for Tables 5 and 7 on consumption.[35] All the coefficient estimates are close to zero and not significant at the conventional levels.[36]

6.4.5. Unweighted results

We also run our main results without weights. Tables E-8 and E-9 present robustness checks for the results on food insecurity (Tables 2 and 4) and consumption (Tables 5 and 7), respectively. The results are qualitatively similar when weights are not used.

7. Policy implications

It is estimated that in North East Nigeria alone, 10.6 million people were in need of some kind of humanitarian assistance in 2020, an increase from the already high 7.9 million in 2019 due to the intensifying conflict exacerbated by the effects of the global pandemic (OCHA, 2021). This puts pressure to the Nigerian government and donors to increase assistance.

Our results have implications for targeting of conflict assistance, but with important limitations. Our descriptive results show that *ex-ante*, household that experience attacks and households that do not, are not significantly different. This implies that household characteristics may

[31] The weight of each animal in the TLU is denoted in parenthesis: camel (1) horse (0.8) cattle (0.7), pigs (0.20), sheep and goats (0.1) turkey (0.03) duck (0.03), poultry (0.01), rabbits and hares (0.02), guinea fowl (0.03). The durable asset index is the first factor of a latent variable model using dummies for the ownership of the following assets: radio, television, refrigerator, sewing machine, computer, stove, bicycle, motorcycle, car, generator, iron, fan, and bed or mattress.

[32] This information is available in the post-harvest visits of the GHS and hence we use the 3-wave panel for the analysis.

[33] We use the double-selection linear regression LASSO where all the variables have been transformed to demeaned variables to correspond to the fixed effects framework in our main regressions. We use cross-validation (CV) to select an optimal value of the LASSO penalty parameter for all LASSOS. Our results are robust to using a plugin iterative formula instead. The results are also robust to using Partialing-out (Belloni et al., 2012; Chernozhukov et al., 2015a,b) and cross-fit partialing-out LASSO linear regression (Chernozhukov et al., 2018) instead of the double-selection model. Results are available from the authors by request. Note that also standard errors are not clustered and the regressions are not weighted.

[34] Columns 2 in table E-2 (table E-3) corresponds to column 3 in Table 2 (Table 5), and columns 3–7 in table E-2 (table E-3) correspond to columns 2, 4, 6, 8, and 10 in Table 4 (Table 7).

[35] To be specific, columns 1–3 in E-6 (table E-7) correspond to columns 2–4 in Table 2 (Table 5) and columns 4–8 correspond to even numbered columns in Table 4 (Table 7).

[36] One coefficient estimates on food insecurity is statistically significant at the 10 per cent level, but of the reverse sign to our main results.

be poor predictors of who have experienced largest setbacks, and information on victimization can play an important role in understanding this, especially given that our results also show that victimized households are affected more than households residing near conflict attacks, who are not directly impacted. Furthermore, our results also show that the extensive and intensive margin differ such that more attacks lead to worse food insecurity and consumption outcomes: households that have experienced attacks multiple times may be in more need. In sum, information on victimization can be used to help identify households who have suffered large setbacks, but other information is required to identify the poorest and those in most need. Indeed, in contexts of fragility, Brück et al. (2019a) and Schnitzer (2019) show that some targeting methods may be better for differentiating the chronically poor from those suffering from transitory poverty. One key limitation of the policy implications of our study is the lack of evidence on the modalities of assistance. Given large market imperfections in fragile settings, the modality also matters: whether cash or food aid is more efficient in reducing food insecurity depends on what kind of constraints households face in their choices of own production and at the markets (Brück et al., 2019a; Schwab, 2019).

In practice, prioritizing emergency aid in fragile settings may be infeasible and difficult to justify. While emergency aid is being delivered to conflict-affected areas in Nigeria, the insecurity in Nigeria is characterized by low-intensity conflict situations that have continued for several years without developing into a war. In such insecure settings, governments' counterinsurgency policies can seek to gain the 'hearts and minds' of the population by service provision or social assistance, with the objective of improving the attitude of the population towards the government and reducing sympathies towards insurgents. In India, the National Rural Employment Guarantee Scheme (NREGS) has been shown to contribute to violence reduction (Fetzer, 2020; Kaila et al., 2020; Dasgupta et al., 2017). Crost et al. (2016) found that the introduction of a conditional cash transfer program reduced conflict in the Philippines.[37]

In West Africa, shock responsive social protection is being designed and piloted in several settings affected by fragility and low-intensity conflict (World Bank, 2020). While these insurance mechanisms are designed for covariate shocks, such as anomalies in climatic conditions affecting farming output, our paper shows that such idiosyncratic shocks as victimization also matter in regions with active conflict. This calls for investigating targeting mechanisms employed in development programs implemented in conflict settings.

8. Conclusions

In this paper, we have analyzed the relationship between victimization and household welfare using panel data from Nigeria. By exploiting variation in the timing and intensity of victimization, we find that attacks against households negatively affect household consumption and increase food insecurity, and that this effect operates independent of conflict in the geographical proximity. Just one additional event can push a household from low to medium food insecurity, and becoming victimized decreases consumption per capita by over 10 percent. Loss of productive assets, namely livestock, is an important intermediary outcome. Meanwhile very few households received any assistance to cope with the shock.

We also find that attacks on property are more detrimental to consumption and food insecurity than violence is. Both violence and property crime are perpetrated by several actors: by insurgents, criminals, and in clashes between farmers and herders. We find that attacks by insurgents are detrimental to the key outcomes of interest. Our key results are conducted using a household fixed effects panel regression and are robust to a placebo tests and several sensitivity and specifications tests.

This paper contributes to the study of extreme poverty by focusing on an increasingly important societal issue keeping people food insecure in the 21st century — fragility, conflict and violence. More than half of the world's poor were estimated to be living under fragility and conflict in 2020, and this share will be increasing significantly (Corral et al., 2020). The nexus of poverty and conflict is thus of increasing importance for policy makers and academics aiming to understand underlying mechanism of poverty today and in the future.

CRediT authorship contribution statement

Heidi Kaila: Data curation, Funding acquisition, Methodology, Software, Writing – original draft, Writing – reviewing and editing, Formal analysis, Visualization. **Abul Azad:** Data curation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.foodpol.2023.102404.

References

Abadie, A., Gardeazabal, J., 2003. The economic costs of conflict: A case study of the Basque country. Amer. Econ. Rev. 93 (1), 113–132. http://dx.doi.org/10.1257/000282803321455188.

Adelaja, A., George, J., 2019. Effects of conflict on agriculture: Evidence from the Boko Haram insurgency. World Dev. 117, 184–195. http://dx.doi.org/10.1016/j.worlddev.2019.01.010.

Ajodo-Adebanjoko, A., 2017. Towards Ending Conflict and Insecurity in the Niger Delta Region: A Collective Non-Violent Approach. Working Paper, African Centre for the Constructive Resolution of Disputes.

Akresh, R., Bhalotra, S., Leone, M., Osili, U.O., 2012. War and stature: Growing up during the Nigerian civil war. Amer. Econ. Rev. 102 (3), 273–277. http://dx.doi.org/10.1257/aer.102.3.273.

Akresh, R., Verwimp, P., Bundervoet, T., 2011. Civil war, crop failure, and child stunting in Rwanda. Econom. Dev. Cult. Chang. 59 (4), 777–810.

Azad, A., Crawford, E., Kaila, H., 2018. Conflict and Violence in Nigeria: Results from the North East, North Central, and South South Zones. Report, World Bank Group, Washington, DC, URL: http://documents.worldbank.org/curated/en/111851538025875054/Conflict-and-Violence-in-Nigeria-Results-from-the-North-East-North-Central-and-South-South-Zones.

Azad, A., Kaila, H., 2018. Food Insecurity in Conflict Affected Regions in Nigeria: Results from the North East, North Central, and South South Zones. Report, World Bank Group, Washington, DC, URL: http://documents.worldbank.org/curated/en/747391538026440063/Food-Insecurity-in-Conflict-Affected-Regions-in-Nigeria-Results-from-the-North-East-North-Central-and-South-South-Zones.

Belloni, A., Chen, D., Chernozhukov, V., Hansen, C., 2012. Sparse models and methods for optimal instruments with an application to eminent domain. Econometrica 80 (6), 2369–2429. http://dx.doi.org/10.3982/ECTA9626.

Belloni, A., Chernozhukov, V., Hansen, C., 2013. Inference on treatment effects after selection among high-dimensional controls. Rev. Econom. Stud. 81 (2), 608–650. http://dx.doi.org/10.1093/restud/rdt044.

Bertoni, E., Maio, M.D., Molini, V., Nisticò, R., 2019. Education is forbidden: The effect of the Boko Haram conflict on education in North-East Nigeria. J. Dev. Econ. 141, 102249. http://dx.doi.org/10.1016/j.jdeveco.2018.06.007.

Blattman, C., Annan, J., 2010. The consequences of child soldiering. Rev. Econ. Stat. 92 (4), 882–898.

Blattman, C., Miguel, E., 2010. Civil war. J. Econ. Lit. 48 (1), 3–57. http://dx.doi.org/10.1257/jel.48.1.3.

[37] However, the evidence is mixed, as studies also find negative effects of some development policies for violence reduction, for example, through insurgents capturing assistance or sabotaging programs (Crost et al., 2014). Security policy may be needed to complement development policy (Kaila et al., 2020).

Brück, T., Cuesta, J., Hoop, J.D., Gentilini, U., Peterman, A., 2019a. Social protection in contexts of fragility and forced displacement: Introduction to a special issue. J. Dev. Stud. 55 (sup1), 1–6. http://dx.doi.org/10.1080/00220388.2019.1687882.

Brück, T., d'Errico, M., Pietrelli, R., 2019b. The effects of violent conflict on household resilience and food security: Evidence from the 2014 Gaza conflict. World Dev. 119, 203–223. http://dx.doi.org/10.1016/j.worlddev.2018.05.008.

Brück, T., Justino, P., Verwimp, P., Avdeenko, A., Tedesco, A., 2015. Measuring violent conflict in micro-level surveys: Current practices and methodological challenges. World Bank Res. Obs. 31 (1), 29–58. http://dx.doi.org/10.1093/wbro/lkv011.

Bundervoet, T., Verwimp, P., Akresh, R., 2009. Health and civil war in rural Burundi. J. Hum. Resour. 44 (2), http://dx.doi.org/10.3368/jhr.44.2.536.

Callen, M., Isaqzadeh, M., Long, J.D., Sprenger, C., 2014. Violence and risk preference: Experimental evidence from Afghanistan. Amer. Econ. Rev. 104 (1), 123–148. http://dx.doi.org/10.1257/aer.104.1.123.

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., Robins, J., 2018. Double/debiased machine learning for treatment and structural parameters. Econom. J. 21 (1), C1–C68. http://dx.doi.org/10.1111/ectj.12097.

Chernozhukov, V., Hansen, C., Spindler, M., 2015a. Post-selection and post-regularization inference in linear models with many controls and instruments. Amer. Econ. Rev. 105 (5), 486–490. http://dx.doi.org/10.1257/aer.p20151022.

Chernozhukov, V., Hansen, C., Spindler, M., 2015b. Valid post-selection and post-regularization inference: An elementary, general approach. Annu. Rev. Econ. 7 (1), 649–688. http://dx.doi.org/10.1146/annurev-economics-012315-015826.

Corral, P., Irwin, A., Krishnan, N., Mahler, D.G., Vishwanath, T., 2020. Fragility and Conflict. On the Front Lines of the Fight against Poverty. World Bank, https://openknowledge.worldbank.org/bitstream/handle/10986/33324/9781464815409.pdf.

Crost, B., Felter, J., Johnston, P., 2014. Aid under fire: Development projects and civil conflict. Amer. Econ. Rev. 104 (6), 1833–1856. http://dx.doi.org/10.1257/aer.104.6.1833.

Crost, B., Felter, J.H., Johnston, P.B., 2016. Conditional cash transfers, civil conflict and insurgent influence: Experimental evidence from the Philippines. J. Dev. Econ. 118, 171–182.

Dabalen, A.L., Paul, S., 2014. Effect of conflict on dietary diversity: Evidence from Côte d'Ivoire. World Dev. 58 (C), 143–158. http://dx.doi.org/10.1016/j.worlddev.2014.0.

Dasgupta, A., Gawande, K., Kapur, D., 2017. (When) do antipoverty programs reduce violence? India's rural employment guarantee and maoist conflict. Int. Organ. 71 (3), 605–632. http://dx.doi.org/10.1017/S0020818317000236.

Douarin, E., Litchfield, J., Gashi, F., 2021. Individual Exposure to Armed Conflict and Entrepreneurship. Technical Report.

D'Souza, A., Jolliffe, D., 2013. Conflict, food price shocks, and food insecurity: The experience of afghan households. Food Policy 42 (C), 32–47. http://dx.doi.org/10.1016/j.foodpol.2013.06.

Ekhator-Mobayode, U.E., Hanmer, L.C., Rubiano, E.C., Matulevich, D.J.A., 2020. The Effect of Armed Conflict on Intimate Partner Violence: Evidence from the Boko Haram Insurgency in Nigeria. Technical Report.

Fetzer, T., 2020. Can workfare programs moderate conflict? Evidence from India. J. Eur. Econom. Assoc. 18 (6), 3337–3375. http://dx.doi.org/10.1093/jeea/jvz062.

George, J., Adelaja, A., Weatherspoon, D., 2019. Armed conflicts and food insecurity: Evidence from Boko Haram's attacks. Am. J. Agric. Econ. http://dx.doi.org/10.1093/ajae/aaz039.

ICG, 2017. Herders Against Farmers: Nigeria's Expanding Deadly Conflict. Africa Report 252, International Crisis Group, Brussels, URL: https://d2071andvip0wj.cloudfront.net/252-nigerias-spreading-herder-farmer-conflict.pdf.

IOM, 2018. Nigeria: Displacement Tracking Matrix Round XXI Report. Report, International Organization for Migration, Grand-Saconnex, Switzerland, URL: https://reliefweb.int/report/nigeria/nigeria-displacement-tracking-matrix-round-xxi-report-february-2018.

Jamison, J., McGee, K., Oseni, G., Perng, J., Sato, R., Tanaka, T., Vakis, R., 2018. The Relationship between Conflicts, Economic Shocks, and Death with Depression, Economic Activities, and Human Capital Investment in Nigeria. Policy Research Working Paper 8685, World Bank Group, Washington, DC.

Kaila, H., Singhal, S., Tuteja, D., 2020. Development programs, security, and violence reduction: Evidence from an insurgency in India. World Dev. 130 (C), http://dx.doi.org/10.1016/j.worlddev.2020.1.

Kirbis, A., Nelson, P., 2022. Individual Exposure to Armed Conflict and Entrepreneurship. Technical Report.

Marc, A., Verjee, N., Mogaka, S., 2015. The Challenge of Stability and Security in West Africa. Report, World Bank; Paris: Agence Française de Développement, Washington, DC, URL: https://openknowledge.worldbank.org/handle/10986/22033.

Martin-Shields, C.P., Stojetz, W., 2019. Food security and conflict: Empirical challenges and future opportunities for research and policy making on food security and conflict. World Dev. 119 (C), 150–164. http://dx.doi.org/10.1016/j.worlddev.2018.07.011.

Maxwell, D., Caldwell, R., 2008. The Coping Strategies Index: Field Methods Manual. Report, Cooperative for Assistance and Relief Everywhere.

Mercier, M., Ngenzebuke, R.L., Verwimp, P., 2020. Violence exposure and poverty: Evidence from the Burundi civil war. J. Comp. Econ. 48 (4), 822–840. http://dx.doi.org/10.1016/j.jce.2020.04.005.

Minoiu, C., Shemyakina, O., 2012. Child health and conflict in Côte d'Ivoire. Amer. Econ. Rev. 102 (3), 294–299.

Minoiu, C., Shemyakina, O.N., 2014. Armed conflict, household victimization, and child health in Côte d'Ivoire. J. Dev. Econ. 108, 237–255.

Nwankpa, M., 2014. The politics of amnesty in Nigeria: A comparative analysis of the boko haram and Niger Delta insurgencies. Contemp. Voices: St Andrews J. Int. Relat. 5 (1).

OCHA, 2018. Humanitarian Needs Overview Nigeria. Report, United Nations Office for the Coordination of Humanitarian Affairs (OCHA), New York, URL: https://www.humanitarianresponse.info/sites/www.humanitarianresponse.info/files/documents/files/13022018_ocha_humanitarian_needs_overview.pdf.

OCHA, 2021. Humanitarian Needs Overview Nigeria. Report, United Nations Office for the Coordination of Humanitarian Affairs (OCHA), New York, URL: https://www.humanitarianresponse.info/sites/www.humanitarianresponse.info/files/documents/files/13022018_ocha_humanitarian_needs_overview.pdf.

Raleigh, C., Linke, A., Hegre, H., Karlsen, J., 2010. Introducing ACLED: An armed conflict location and event dataset: Special data feature. J. Peace Res. 47, 651–660. http://dx.doi.org/10.1177/0022343310378914.

Rockmore, M., 2016. The cost of fear: The welfare effect of the risk of violence in Northern Uganda. World Bank Econ. Rev. 31 (3), 650–669.

Rockmore, M., Barrett, C.B., Annan, J., 2017. The Implications of Aggregate Measures of Exposure to Violence for the Estimated Impacts on Individual Risk Preferences. Technical Report.

Schnitzer, P., 2019. How to target households in adaptive social protection systems? Evidence from humanitarian and development approaches in Niger. J. Dev. Stud. 55 (sup1), 75–90. http://dx.doi.org/10.1080/00220388.2019.1687877.

Schwab, B., 2019. Comparing the productive effects of cash and food transfers in a crisis setting: Evidence from a randomised experiment in Yemen. J. Dev. Stud. 55 (sup1), 29–54. http://dx.doi.org/10.1080/00220388.2019.1687880.

Serneels, P., Verpoorten, M., 2015. The impact of armed conflict on economic performance: Evidence from Rwanda. J. Confl. Resolut. 59 (4), 555–592. http://dx.doi.org/10.1177/0022002713515409.

Singhal, S., 2019. Early life shocks and mental health: The long-term effect of war in Vietnam. J. Dev. Econ. 141, 102244. http://dx.doi.org/10.1016/j.jdeveco.2018.06.002.

Trudell, J.P., Burnet, M.L., Ziegler, B.R., Luginaah, I., 2021. The impact of food insecurity on mental health in Africa: A systematic review. Soc. Sci. Med. 278, 113953. http://dx.doi.org/10.1016/j.socscimed.2021.113953.

Verwimp, P., 2012. Undernutrition, subsequent risk of mortality and civil war in Burundi. Econ. Hum. Biol. 10 (3), 221–231.

Verwimp, P., Justino, P., Brück, T., 2019. The microeconomics of violent conflict. J. Dev. Econ. 141, 102297. http://dx.doi.org/10.1016/j.jdeveco.2018.10.005.

Weissman, M.M., Sholomskas, D., Pottenger, M., Prusoff, B.A., Locke, B.Z., 1977. Assessing depressive symptoms in five psychiatric populations: a validation study. Am. J. Epidemiol. 106 (3), 203–214.

World Bank, 1986. Poverty and Hunger: Issues and Options for Food Security in Developing Countries. Report, World Bank, Washington, DC, URL: http://documents.worldbank.org/curated/en/166331467990005748/Poverty-and-hunger-issues-and-options-for-food-security-in-developing-countries.

World Bank, 2020. Sahel Adaptive Social Protection Program Annual Report 2020. Report, World Bank, Washington, DC, URL: https://socialprotection.org/sites/default/files/publications_files/SASPP%202020.pdf.