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Conflict, Household Victimization, and Welfare: Does the Perpetrator Matter?

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HiCN Working Paper 314

September 2019

Abstract: This paper studies the relationship between conflict and household welfare by using a detailed panel data set of household victimization across the most conflict-affected regions in Nigeria between 2010 and 2017, during a time characterized by a sharp increase in conflict. The North East region has been hardest hit with the recent Boko Haram insurgency. The North Central region has seen clashes between herders and farmers over land and resources. Several militant groups operate in the oil-producing Niger Delta region, where their aim is to extract resources by disrupting oil production. By exploiting the plausibly exogenous variation in the timing, intensity, and spatial distribution of victimization, we find that becoming a victim of conflict leads to higher food insecurity and decreased consumption. Since different types of actors have different motivations for their actions, the consequences of victimization might vary depending on the perpetrator. We find that events perpetrated by insurgents are the most detrimental to consumption, whereas food insecurity increases as a consequence of both insurgent and criminal activity. This is in line with the results being strongest in the North East, which also has the highest intensity of conflict. We also find that property-related events are more detrimental to consumption and food insecurity than are violent events. Likewise, we find suggestive evidence that violent events, as well as events perpetrated by insurgents and bandits, are detrimental to mental health. Our findings highlight the importance of collecting nuanced information of victimization in conflict- affected areas.

JEL classification: I32, O12

Keywords: conflict, victimization, food insecurity, consumption, mental health, Nigeria

Acknowledgements: We thank Chris Barrett, John Hoddinott, Carlos Rodríguez-Castelán, Vasco Molini, Nadia F. Piffaretti, Christopher Boone, Saurabh Singhal, Smriti Sharma, Clement Joubert, and participants at the 2019 Centre 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 and Michael Wild for their work on the sampling and Aibek Baibagysh Uulu for the work on the consumption aggregate. Kaila gratefully acknowledges financial support from Danmarks Frie Forskningsfond (DFF). The authors are responsible for any remaining errors.

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1. Introduction

Armed conflict can have severe consequences to household welfare in conflict-affected areas. These negative consequences for local populations are indisputable (Blattman and Miguel 2010; Verwimp, Justino, and Brück 2018). However, the dynamic effects of victimization on household welfare remain understudied because longitudinal data about victimization is still scarce. Furthermore, the differential impacts of different types of victimization, ranging from violent attacks to attacks on property, are not well-known. Not all attacks against civilians in conflict-affected areas are committed by the main actors of the conflict. In conflict situations, crimes become more prevalent when law enforcement weakens and the opportunity cost of criminal activity decreases. Yet little is understood about how attacks committed by different types of perpetrators affect household welfare.

In this paper, we present microeconomic evidence on the effect of different types of victimization and different types of perpetrators on household welfare. Using panel data collected before, during, and after a large increase in conflict, we exploit plausibly exogenous variation in the timing, location, and intensity of household exposure to conflict to analyze the effects of victimization on household welfare. We conduct the analysis using panel data from the three most-conflict-affected regions in Nigeria, which all have witnessed an increase in conflict and violence since 2010.

Our first contribution to the literature is to quantify the effects of victimization on household consumption and food insecurity. We find that one additional conflict event leads to a 3–4 percent decrease in consumption. Both food and nonfood consumption are affected by victimization. By defining poverty as a threshold level of US$1.90 per capita per day consumption, we also find that poor households are more likely to stay poor after becoming victimized, whereas nonpoor households manage to prevent themselves from falling into poverty. We also find evidence of increased health and decreased educational expenditures relating to the herder-farmer clashes. This is in line with literature that documents a relationship between conflict and decreased schooling (Ichino and Winter-Ebmer 2004; Chamarbagwala and Moran 2011; Shemyakina 2011; Swee 2015; Monteiro and Rocha 2017; Bertoni et al. 2018).[1]

[1] An effect not observed in a lower violence setting in Mexico (Márquez-Padilla, Pérez-Arce, and Rodríguez-Castelán 2015).

Most of the literature about the effects of conflict on household welfare use regionally recorded conflict measures. Our study contributes to the growing literature about the effects of victimization on well-being (Blattman and Annan 2010; Minoiu and Shemyakina 2012, 2014; Rockmore 2017). More broadly, our study contributes to the literature about the effect of conflict on poverty and well-being as a consequence of war (Justino 2012; Serneels and Verpoorten 2013; Mercier, Ngenzebuke, and Verwimp 2016) and as a consequence of low-intensity conflict (Enamorado, López-Calva, and Rodríguez-Castelán 2014; Martínez-Cruz and Rodríguez-Castelán 2016).

We study food security in addition to consumption because it might measure a slightly different type of vulnerability. Food security can be either chronic or transitory (World Bank 1986). The former is associated with problems of continuing or structural poverty and low incomes; the latter refers to periods of intensified pressure caused by shocks, such as natural disasters, economic collapse, or conflict. We find a strong and robust effect of victimization on food insecurity using up to six rounds of data. Earlier evidence finds a strong relationship between child nutrition and conflict by exploiting the differential variation in the timing of birth relative to conflict (Bundervoet, Verwimp, and Akresh 2009; Akresh, Verwimp, and Bundervoet 2011; Akresh et al. 2012; Verwimp 2012; Minoiu and Shemyakina 2012, 2014; Akresh et al. 2017). Yet evidence on household food insecurity remains mixed. Dabalen and Paul (2014) find negative consequences of victimization on food insecurity, and D'Souza and Jolliffe (2013) find a relationship between conflict and food security in Afghanistan despite the fact that provinces with high conflict intensities are relatively more food secure. Brück, d'Errico, and Pietrelli (2019) find no effect of conflict on food security as a consequence of the 2014 Gaza conflict.[2] Our paper makes an important contribution to this literature by having a long panel data set. The empirical strategy is well suited for our measure of food insecurity: the Coping Strategies Index, or CSI (Maxwell and Caldwell 2008). The index is constructed from questions measuring behavior—mainly, how many coping strategies and how often a household needed to use them during the preceding seven days—and it is therefore particularly useful for detecting changes over time (Maxwell and Caldwell 2008; Barrett 2010).

In a context with low-intensity conflict, acts of violence and crime are committed by different types of perpetrators, each of whom have different motivations for their acts. Insurgents

[2] For a recent review, see Martin-Shields and Stojetz (2019).

typically justify their acts by political or religious motivations toward a larger societal goal. Communal violence, on the other hand, often arises from disagreements about the distribution of resources within a community; it might also be fueled by ethnic, religious, or political arguments. Alongside increased insecurity, the opportunity cost of criminal activity increases as a consequence of the reduced capacity of law enforcement. Therefore, crimes committed in conflict-affected areas also might be motivated by purely personal economic gains. Different groups might be committing crimes and violence for different purposes in conflict-affected areas. These acts might lead to different outcomes depending on the motivations of the perpetrators.

Our second contribution is to quantify the effects of different types of conflict and victimization to understand what kinds of attacks and what types of perpetrators are most detrimental to well-being. Nigeria provides an excellent 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 it 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 increasing tensions between herders and farmers also pose important threats to national security. Our data contains information on the types of violent and other criminal events to which the households have been subjected. Furthermore, the data set contains information about the perpetrator of the event. We find 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 the farmer-herder conflict. This is in line with the results also being strongest in the North East, which has the highest intensity of Boko Haram activity and, overall, the highest occurrence of conflict events. The insurgency, however, has been active elsewhere in the country, particularly in the North Central area. We also find that events related to property, such as theft or the destruction of assets, are more detrimental to food insecurity and consumption than are violent events.

We also were interested in studying mental health as an outcome of conflict because economic well-being and mental health are strongly connected (Alloush 2019). Becoming a victim of crime and violence can lead to trauma. Recent studies have established a link between conflict exposure and mental health (Singhal 2018; Jamison et al. 2018). For our measure of mental health, we use the Center for Epidemiologic Studies Depression Scale (CES-D), which was introduced in wave 3 of the General Household Survey (GHS) (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). We find that victimization is related to a higher level of symptoms of depression. It is also possible that the extent of trauma following an event varies across different types of events. Indeed, contrary to our results on economic well-being, we find that whereas violent attacks are related to lower mental health, property-related events are not. Furthermore, as the motivations of different perpetrators can vary, the consequences of their attacks might also differ. Indeed, we find that events perpetrated by insurgents, bandits, and criminals are related to lower mental health, but those of communal clashes are not. Our findings highlight the importance of further studying the links between the economic and mental health consequences of victimization.

Our third contribution relates to the method of collecting the data. The victimization data used in the study is from a telephone survey among households that were part of the GHS panel collected between 2010 and 2016 (a Living Standards Measurement Study, or LSMS, data set by the World Bank). Information on household welfare and characteristics before, during, and after the conflict comes from the GHS panel. We have complemented this data with annual telephone survey data on the recall of victimization dating back to 2010.

Our data is also novel because we collected the information about household victimization over the phone;[3] this was considered a strong alternative to face-to-face interviews because close to 90 percent of all households in the GHS regions had phones. In addition, phone surveys have several advantages. Survey fatigue is less of an issue when interview time is short and the topic is limited to victimization only. Also, talking about conflict events might be psychologically burdensome, which is why keeping the interview short is particularly important. Finally, people living in conflict-affected areas might be afraid to be seen reporting these events to enumerators who work for the Nigerian government; therefore, they might feel more comfortable reporting such sensitive events over the phone. Administering the conflict module in a separate telephone-based survey allowed us to get detailed information on the events, without placing a large burden to the households during a long household interview.[4]

[3] Similar telephone surveys have been conducted in six countries in Sub-Saharan Africa under the World Bank project Listening to Africa (Croke et al. 2012).

[4] Telephone surveys would also be recommended in situations with high migration, which might lead to systematic attrition. The migration rates in the LSMS panel were very low between 2010 and 2016, and in our telephone survey sample, all households had stayed in the same local government area since 2010.

We estimate the effects of household victimization on consumption expenditure variables and food insecurity using household fixed effects to control for all time-invariant household characteristics. Additionally, we augment this specification with a large number of time-varying controls for geographical variables, such as rainfall and temperature, as well as time-varying household characteristics. The results change little from the fixed effects specification when adding controls and survey year-region fixed effects, which account for differing common trends in the regions studied. Even though the fixed effect framework does not require the households to be similar at the baseline, we find that victimized and nonvictimized households are similar in characteristics at the beginning of the data collection, while conflict events are geographically clustered. Thus, the risk of becoming a victim is *ex ante* not related to our outcome variables of interest nor to household characteristics.

Our results are obtained using weighted regressions to account for the sampling strategy. However, they are robust to unweighted regressions. are also robust to alternative lag structure on victimization. Results on food insecurity are robust to an alternative transformation of the CSI index and to an alternative sample specification.

This article proceeds as follows: Section 2 discusses the evolution of conflict in the three regions of Nigeria. Section 3 presents the data used for the analysis. Section 4 presents the empirical framework. Section 5 presents the results. Section 6 is the conclusion.

2. Conflict in Nigeria

With more than 180 million inhabitants, Nigeria is the most populous country in Africa and the largest economy as measured by GDP. Ethnicity and religion have played a role in the history of conflict in Nigeria at least since independence. 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 recently seen a 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, Verjee, and Mogaka 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 (the zones selected for the telephone survey). These regions have all seen an increase in conflict levels since 2010.[5] In the North East, conflict is largely attributable to Boko Haram. The violent radicalization of Boko Haram members and the resulting military operations have reportedly 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, an estimated 20,000 people have been 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 2017). Our data indicates that 49 percent of households in the North East had been a victim of a conflict event 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.

In the North Central region, the conflict centers around agricultural households and nomadic cattle-herding groups who come into conflict over land and water access. Over the past few years the conflict has been increasing between these two groups. Farmland has been destroyed and forcefully occupied, livestock has been stolen, and crops have been damaged. The conflict has intensified as many northern herdsmen have moved their herding routes toward the south. There have been multiple push factors: the Boko Haram insurgency in the North East, the growth of human settlements in the north more broadly, and the degradation of pastures in the north due to droughts. The death toll has been increasing, with 2,500 fatalities recorded in 2016 alone (International Crisis Group 2017).

Our data indicates that 25 percent of households in the North Central region experienced at least one conflict event between 2010 and 2017. The most common perpetrators of the event are reported to be pastoralists or nomads (45 percent), and the second most common perpetrators are insurgents (21).[6] This indicates that the Boko Haram insurgency also has been active in the North Central region, but to a lesser degree than in the North East.

[5] Appendix B provides more details on the spatial and time variation of conflict in the three regions with comparisons to external data sources.

[6] 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.

In the South South region—that is, in the Niger Delta area—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 is 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). However, new militant groups have emerged since, and fatalities have increased during the last few years (figure B.1).

In the Niger Delta region, 22 percent of households in our data reported at least one conflict event between 2010 and 2017, a similar figure to the conflict intensity in the North Central region. Bandits and criminals were the most common type of perpetrator (42 percent of cases).

3. Data

3.1. Data sources

We combined the GHS panel data with data from a telephone survey on household victimization that was conducted with a subset of the GHS panel households during 2017. The GHS is an LSMS data set that has been collected in three waves between 2010 and 2016. The waves are 2010–11, 2012–13, and 2015–16, and they include two visits each: a postplanting visit during the autumn months and a postharvest visit during the spring.

A separate telephone-based conflict survey was administered to 717 of the GHS panel households selected from the most recent visit (wave 3, visit 2).[7] The purpose of the survey was to understand the extent to which households experienced conflict: whether they had become victims of violence or property-related crime or if they had experienced other events related to conflict and criminal activity since 2010. These events are thus based on participants' recall of the period between January 2010 and May 2017. Participants were asked to recall events that occurred each year during this span. The survey covered the three most conflict-affected geographical zones within the 16 states of Nigeria.[8] Households from local government areas (LGAs) that had high conflict exposure were oversampled based on

[7] The GHS waves include between 4,500 and 5,000 households. During the last visit—the second visit of the third round—the sample size was 4,579.
[8] The telephone-based survey was conducted between March and May 2017. See appendix B for details on how the geopolitical zones were selected based on conflict exposure.

the following criteria: they needed to have more than 10 conflict events during 2012–14 recorded in the Armed Conflict Location & Event Data Project (ACLED) database (Raleigh et al. 2010).

Conflict-affected areas were oversampled to create a sample of individuals who had experienced conflict events to shed light on the types of events that had occurred. A random sample of the zones might have presented an insufficient sample of conflict-affected households; this, therefore, would have restricted the analysis of the types of conflict events. Due to the oversampling, however, the sample drawn was not representative at the level of the geopolitical zone, as is the case in the GHS. Indeed, out of the 717 households that are spread across 99 LGAs, all conflict events were concentrated in 52 LGAs—that is, almost half (47) of the LGAs did not have any household conflict exposure. This suggests strong geographical clustering of conflict events.[9] Even though the conflict was widespread in these areas, the LSMS 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 of the LSMS panel.

To account for the biases arising from the sampling, we present our results using probability weights. This renders the estimates representative at the level of the geopolitical zone (North East, North Central, and South South), as is the case with the GHS panel. 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 the biases arising from the oversampling of the high-intensity conflict LGAs, for nonresponse, and for the fact that a minority of the households surveyed in wave 3, visit 2, of the GHS 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.[10] Additionally, in appendix E we show that the results are robust to unweighted regressions. Appendix A, section 2, provides additional information on the administration of the telephone survey.

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

[10] In the North East, the mobile phone penetration rate is 84 percent. In the North Central and South South regions, it is 90 percent and 83 percent, respectively.

3.2. Descriptive statistics

Conflict has increased in all regions as measured by the mean number of events a household has experienced. Figure 1 shows us the evolution of conflict events between 2010 and spring 2017. Figure 1, panel a, displays the data of all events as well as property- and violence-related events. We can see that from 2012 onward, the level of household victimization has greatly increased.

Figure 1, panel b, displays the mean number of events per year by the most common types of perpetrators: insurgents, bandits and criminals, and pastoralists and nomads. We can see that events in which the perpetrator was an insurgent peaked in 2014, which corresponds to the most violent year of the Boko Haram insurgency. The number of events involving bandits and criminals is increasing over time. The number of events involving pastoralists and nomads increased in 2013 and has remained at that level. It is noteworthy to point out that the decrease in 2017 is not representative of the entire year but only until May 2017 (see figure 1, panels a and b). It is meaningful to study the perpetrator and the type of event separately because both violent and property-related events are perpetrated by all types of perpetrators.[11]

There are potential limitations in measuring victimization that merit discussion. If past events are not remembered as well as more recent events, our data might suffer from recall bias. To address this issue, we compare the time distribution of victimization to the conflict intensity from the ACLED database at the annual level. Figure B.1 in appendix B displays the time distribution of the events; the vertical axis shows what fraction of all events recorded between 2010 and 2016 for the data set in question happened in each specific year. This way of analyzing the data yields a meaningful comparison between our data set and the ACLED database, as ACLED collects data on the number of conflict events and fatalities reported by newspapers and thus without recall bias. However, the different measures mean we cannot compare *the levels* of conflict across the data sets. Nonetheless, we can see that the time trend in both conflict events and fatalities in the ACLED is similar to the time trend of our measure of victimization. Although it is impossible to fully rule out recall bias, we are not too worried

[11] Although violent events are most often perpetrated by insurgents (30.5 percent of all violent events 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 property-related events are most often perpetrated by pastoralists and nomads (38.7 percent), 20.5 percent and 22.3 percent of property-related events are perpetrated by insurgents and bandits and criminals, respectively.

about it because the conflict intensities have evolved similarly across the data sets. Any presence of recall bias, however, would bias down our estimation results.

We also compare the spatial distribution of the events between our data set and the ACLED database, which was used as our basis for selecting the most appropriate geopolitical zones for the telephone survey. By comparing figure B.2, panel a (the number of events in the ACLED data set) and panel b (household victimization in the telephone survey), we can indeed see that 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, our victimization measure almost certainly excludes certain types of victimization. First, 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. Second, we have very low reports of police or military violence; this might also be underestimated because the telephone survey was administered by the government.

The data also shows that many events reported in the survey were not reported to anyone in the community, including community and religious leaders as well as authorities.[12] Given that the number of conflict-event reports in the survey are 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 LSMS/National Bureau of Statistics (NBS) survey teams since 2010—that is, prior to the telephone survey—which surely helped build trust. However, keeping in mind that households might be underreporting some specific types of events, our victimization measure—and therefore also our estimation results—might be downward biased.

The evolution of the consumption levels is displayed in figure 2, panel a, over the three waves of the analysis. We can see that consumption has been increasing in all three regions, but it is especially rapid in the South South.

Figure 2, panel b, shows the evolution of the CSI over time. The CSI is a simple tool to assess food insecurity by measuring behavior. The basic logic is to answer this question: "What do you do when you don't have enough food and don't have enough money to buy food?" The

[12] Among the 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 event to any authority.

CSI measures how often during the previous seven days the household had to resort to any coping strategy listed in the questionnaire, based on the idea that the more people have to cope, the greater their food insecurity.[13] The CSI is a suitable tool to track and monitor trends in food insecurity within the same population over time. 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, we find that over 20 percent of households suffer either from medium or high food insecurity, with a slight increase over time.[14] From summary statistics (see table 1, panel b), we can see that the mean household in any of the regions in any given visit was not highly food insecure, scoring a mean index value of 2.87.

Summary statistics for the key variables of interest are presented in table 1, panels a and b, for the wave-based consumption analysis and for the round-based food insecurity analysis, respectively. Panel c reports the CES-D score, which is measured only in wave 3. 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.[15] In any given wave, the households experienced on average 0.21 conflict events per wave, with the highest incidence being in the North East and the lowest in the South South. We can see that property-related events are more common than violent events, and both of those event types are most common in the North East.

Events 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. Events perpetrated by bandits and criminals occur in each region, but they also are most prevalent in the North East. Events perpetrated 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.

Table 1, panel c, presents the summary statistics for the CES-D score. The score takes values from 0 to 30, with higher values reflecting poor mental health. We can see that the CES-D

[13] The questions are listed in appendix A.
[14] For consistency, data from wave 1, visit 1, are omitted from this figure because they are omitted from the analysis.
[15] 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.

score was the highest in the North East, but the mean values are quite similar in all regions. A CES-D index of above 10 is regarded as a threshold level for significant depressive symptoms. In our sample, 28 percent of the respondents have a score above this level, so poor mental health is indeed a common issue in the regions studied.[16]

Looking at the demographic characteristics in table 1, panels a and b, we can see that the 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 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 being in the North East and the lowest in the South South. These descriptive statistics illustrate the regional differences between Nigeria's poorer north and relatively wealthier south.

4. Empirical framework

4.1. Panel data sets

For the analysis, we created two panel data sets: one for the consumption measures, including poverty, and one for food insecurity as outcome variables. The outcome variables were measured at different points in time. Figure D.1 in appendix D illustrates the timing of the data in terms of the outcome variables as well as the telephone survey.

For consumption, we have data from three waves that have two visits each; one visit is in the autumn (postplanting), and the other is in the spring (postharvest). The consumption aggregate is the median of the consumption level of those two visits. Hence, we have a measure for consumption at three points in time (2010–11, 2012–13, and 2015–16). Our food insecurity measure, the CSI, comprises the seven-day recall questions administered during each visit of the GHS—that is, altogether six times during the GHS panel (autumn 2010, spring 2011, autumn 2012, spring 2013, autumn 2015, and spring 2016). For simplicity, in referring to this panel in the paper, we talk about *rounds* to refer to the wave-visit frequency. Given that in our estimation strategy we are interested in the lagged conflict events to alleviate concerns of reverse causality, we are dropping the CSI measured in 2010 from the analysis because no conflict information exists for 2009.[17] Figure D.2, panels a and b,

[16] See Jamison et al. (2018) for more analysis with this data.
[17] That is, for the postharvest visit of GHS wave 1 (spring 2011), we include events in 2010. For GHS wave 2, visit 1 (autumn 2012), events in 2011 were included, and for wave 2, visit 2 (spring 2013), events in 2012 were

illustrate the timing of the merge between the outcome variables and the victimization data sets for the wave-based and the round-based panel data sets, respectively.[18]

4.2. Empirical model

To assess the effect of household conflict events on consumption and food insecurity, we run a fixed effects model of the following form

$$Y_{i,r,t,w} = \alpha_i + \beta \sum_{j=w-1}^{t-1} Conflict_{i,j} + \boldsymbol{\gamma X}_{i,r,t,w} + \theta_w + \tau_{\boldsymbol{r},w} + \varepsilon_{i,r,t,w} \qquad (1)$$

where $Y_{i,r,t,w}$ is either (log) consumption 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 are denoted as θ_w (for waves for the consumption analysis and for round—that is, wave and visit—for the food insecurity analysis). The variable $\sum_{j=w-1}^{t-1} Conflict_{i,j}$ records the number of conflict events 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 $t-1$). Therefore, our victimization measure captures the intensity of victimization as measured by the number of events.

4.3. Threats to identification

Although household fixed effects capture all time-invariant household characteristics, we also control for time-varying household and geographic characteristics, $\boldsymbol{\gamma X}_{i,r,t,w}$. The household controls are household size, household head gender and age, household head education in years and employment status, and dummies for different marital statuses (as listed in table 1). We display results both with and without controls because some controls could be "bad controls," meaning they could be directly affected by conflict. This is the case, for instance, with widowhood and employment status. Additionally, we also control for geographical time-

included. For wave 3, visit 1 (autumn 2015), events in 2013 and 2014 were included, and for wave 3, visit 2 (spring 2016), events in 2015 were included.

[18] Figure D.2, panel a, illustrates how events that occurred in 2010 are merged in wave 1 (2010–11), events recorded in 2011 and 2012 are merged with wave 2 (2012–13), and finally events that occurred in 2013, 2014, and 2015 are merged with wave 3 (2015–16). Therefore, events that occurred in 2016 and 2017 are dropped from the analysis, as they have occurred mostly after the end of the last visit for data collection in spring 2016.

[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 conflict 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.

varying factors at the household level, such as temperature and precipitation, factors that could directly affect our outcome variables (see the variables in table A.1). Finally, we also consider that there might be regional trends that correlate with conflict intensity, which is why we also control for 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 further confounded by the fact that a household might receive assistance from informal safety nets after a conflict event. To understand how receiving assistance might affect our findings, we run alternative specifications by removing households that reported any such assistance after the most recent event (from the telephone survey) as well as households that reported having received either cash or in-kind transfers in the GHS panel. A small subset (just 6 percent) of the households reported any assistance.

Even though our fixed effect estimators remove the time-invariant household characteristics, we are still interested in examining whether the targeting of households was systematically driven by household characteristics. We do so by investigating the differences across households that experienced any conflict during the survey period and those that did not by running a t-test with our outcome variables of interest and with a number of household and geographical characteristics related to the household's location. We find that in 2010–11, households that were exposed to conflict at any time during the survey were indeed similar to those not exposed to conflict.

The results are reported in appendix C, table C.1. Panel a compares household characteristics, and panel b compares household location-specific geographical characteristics.[20] We can see from panel a that in the first round of the GHS, there are no statistically significant differences in the poverty status, level of consumption, and the CSI between households that had experienced conflict events between 2010 and 2017 and households that had not. We find only a couple of statistically significant differences in household characteristics across these samples. Larger households and polygamous households were more likely to have experienced conflict events. This is unsurprising because our conflict indicators include variables such as a household member being robbed or a household member being injured due to an attack. Larger households (a variable that correlated strongly with polygamy)

[20] The summary statistics and the description of the geographical variables are presented in appendix A, tables A.1 and A.2, respectively.

should have a higher probability of such incidents having occurred to individual household members simply because these households have more members.

From panel b, we can see that the geographical characteristics of households that have experienced conflict and those that have not vary somewhat in 2010–11, as we might expect given the geographical clustering of the conflict events to around 50 percent of the LGAs in the sample. These variables are related to exogenous conditions such as rainfall and temperature. 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.[21] Likewise, we control for all household demographic characteristics in table C.2 (household size; household head gender, age, and years of education; area of residence; and dummies for marital status and employment status) as well as asset ownership, which we do by constructing an asset index using factor analysis[22] and a dummy denoting whether the household owns livestock.

It is clear from the baseline t-test in table B.1 that household welfare, as measured by food insecurity or consumption or any of its subcomponents, was not *ex ante* correlated with conflict exposure. Thus, we may assume that even though conflict is clustered geographically, the targeting of households within a given LGA is more random. However, this is not required for identification because household fixed effects absorb the location-specific time-invariant differences across households.

As a robustness check, we also consider an alternative specification of conflict recall, where we estimate the effects of only period $t-1$ conflict events on the outcome variables measured at time t. Because the data was not collected across evenly spaced time intervals, doing so makes the specification more uniform across the waves. This empirical specification is described in detail in section 5.4.4, and appendix F, figures F.1 and F.2, illustrate the timing. The results of this check are also presented in appendix F.

[21] The summary statistics of the geographical variables are presented in appendix A, table A.1.
[22] The 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.

5. Results

5.1. Food insecurity

We estimate the relationship between conflict and food insecurity using the round-based panel because the CSI data have been collected in each wave and visit to measure seasonal changes in food insecurity. Table 2 shows the results from estimating the effect of victimization on the standardized CSI and the (standardized) components used in constructing the index. An additional conflict event is associated with the increase in the CSI by around 0.044 to 0.052 standard deviations (table 2, columns 1–3). 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, column 3).

After a conflict event, a household might receive assistance from informal safety nets to overcome the event's consequences. In order to understand how receiving assistance might affect our findings, in column 4 of table 2 we removed households that reported having received any assistance after the most recent event (from the telephone survey) as well as households that reported having received either cash or in-kind transfers in the GHS panel. A small subset (only 6 percent) of the households reported any assistance. Removing these households from the sample brings down the coefficient estimate to 0.038 standard deviations, but the result remains significant at the 5 percent level. This suggests that households that received any form of 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 the household coping strategies used after a conflict event are most often the kind 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, results that are in line with the low level of assistance reported after a conflict event.

In table 3 we analyze whether the effects of victimization on food insecurity vary by event type and across perpetrators. Property-related events include robbery of dwellings and individuals, having one's dwelling destroyed or occupied, having one's land occupied or destroyed, and having household assets destroyed. Violent events include killings, injuries, and physical aggression.[23] Furthermore, we run the analysis by the perpetrator of the event.

[23] The rest of the event categories include sexual violence and a household member being forced to work, being kidnapped/abducted, being made a refugee or internally displaced, and being restricted from going to school or

The most commonly reported perpetrators in our data are insurgents, bandits and criminals, and pastoralists and nomads.[24] It is possible that the same household has been exposed to different types of events perpetrated by different actors. In our empirical specification we therefore compare households that have experienced, for example, property-related events (and possibly other events) with households that have not experienced property-related events (but might have experienced other events).[25] This allows us to compare the magnitude of different types of events.

In columns 1–4 in table 3, we report the results of the most common types of events, property-related and violent events. Columns 5–10 show results split by the perpetrator of the event. We can see that property-related events lead to increased food insecurity more strongly than violent events do. Our results are in line with those of D'Souza and Jolliffe (2013) and Dabalen and Paul (2014), who find a negative relationship between conflict and food security in Afghanistan and Côte d'Ivoire, respectively. In columns 5–10, we can see that the results are strongest for the events in which the perpetrator was a bandit/criminal or an insurgent, relative to a pastoralist/nomad. The results are significant at the 1 percent level. The coefficient estimates of the insurgents are slightly higher than those for all events combined (table 2), whereas in the case of bandits/criminals, the effects are larger.

Note that in conflict-affected areas, conflict might affect the food insecurity of *all* households to some extent. Our results therefore illustrate the added effect of becoming a victim of conflict. Evidence suggests that in areas with active Boko Haram insurgency, food production has reduced (Adelaja and George 2019). In these areas, markets might operate less efficiently, resulting in disruptions to food supply. Finally, it could also be that net-buyer households that rely on markets as their main source of food are less able to purchase goods at the markets due to lower purchasing power resulting from lower income or increased food inflation. Azad and Kaila (2018) document suggestive evidence for this channel: households

seeking health care services. There are no reports of sexual violence. This is likely because most of the respondents in the survey were household heads and, particularly in the North East, male. Limitations to our data collection from the gender perspective are discussed in detail in an adjacent data report (Azad, Crawford, and Kaila 2018).

[24] 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.

[25] We have also run the analysis so that we are dropping from the comparison group in each regression the households that have experienced other events, such that the comparison is between violent events and no events, and property-related events and no events, and so forth. The results are similar and are available from the authors by request.

report food inflation to be a strong concern related to access to food, which is in line with high food inflation rates in 2016–17.

5.2. Consumption

Table 4 shows the results for estimating the relationship between conflict and (log) consumption. We can see that one additional conflict events decreases consumption by 3.2–3.8 percent (columns 1–3). In column 4, we removed households that reported having received any assistance after the most recent event, similarly as in table 2. We can see again that the magnitude drops slightly, to 2.3 percent. This is consistent with the food insecurity results; it seems that households that received any assistance at some point had been harder hit. Columns 5–8 in table 4 break the results between food and nonfood consumption. We can see that both forms of consumption are affected by victimization, with a slightly stronger decrease in nonfood consumption.

Table 5 reports the results from a model with events split by the type (columns 1–4) and the perpetrator of the event (columns 5–10). We can see from columns 1 and 2 that the decrease in consumption is driven by property-related events more than by violence, with a 6.6–8.7 percent decrease in consumption for an additional conflict event. The coefficient estimates for the violent events are negative, but they are not statistically significant.

Columns 5–10 show the same models, splitting the conflict events by the main type of perpetrator. We can see that the results are clearly the strongest when the perpetrator is reported to have been an insurgent. An event perpetrated by insurgents leads to a decrease in consumption 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 events 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.

For reference, Serneels and Verpoorten (2013) find that households that experienced high violence in their localities during the Rwandan genocide in 1994 had at least 28 percent lower consumption levels in 2000 than did households that experienced no conflict. Mercier, Ngenzebuke, and Verwimp (2016) find that the exposure of a locality to conflict during the Burundi civil war (1998–2007) is associated with at least a 9 percent decrease in household consumption in 2012. Our coefficient estimates are smaller in magnitude than in Rwanda and Burundi, countries that experienced a genocide and a prolonged civil war, respectively.

However, the coefficient estimates are qualitatively different, as victimized households have on average experienced more than two events. This implies that households that have experienced multiple events have experienced a decrease in consumption higher than 3.5 percent, a loss associated with one additional event.

5.3. Additional results

5.3.1. Health and education expenditures

To understand what is driving the results on the nonfood consumption expenditures, we look at two important components: health and education expenditures. The results are presented in table 6. We find that conflict events as a whole do not have an effect on health expenditures (column 1). Disaggregated results show, however, that when perpetrators are nomads, there is a statistically significant increase in health expenditures by as much as 21.5 percent. Similarly, conflict events as an aggregate lead to only a marginally significant decrease in education expenditures of 17 percent (column 2). Disaggregated results (columns 3–7 for health and columns 8–12 for education) show that property-related events lead to a decrease in education expenditures by as much as 55 percent. Disaggregating the results by perpetrator shows coefficient estimates of almost equally high magnitudes, but only in the case where the perpetrators are nomads is the coefficient estimate significant at the 10 percent level. The results on the nomads highlight that households targeted by herder-farmer violence increase their health expenditures after 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 do not lead to changes in these variables might be indicative of the poor situation of health care and education in the regions where Boko Haram has been active. Both schools and primary health care centers have been attacked by insurgents, and this has led to lower educational attainment in these areas (Bertoni et al. 2018).

5.3.2. Mental health

Next, in table 7 we investigate the relationship between conflict events in 2010–16 and the 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 suggestive. The odd-numbered columns of table 7 present the results without controls. The even-numbered columns add household and geographical controls for waves 3, 2, and 1 separately as well as geographical controls for wave 3 and zone fixed effects. The CES-D score is in logs. We can see that an additional conflict event is related to poorer mental health, a 4.6 percent higher CES-D score. This result is significant at the 5 percent level and is perfectly robust to adding controls. We also find that violence is related to a 17–18 percent higher CES-D score, and this result is significant at the 1 percent level. We do not find a statistically significant relationship between property crimes and mental health. Overall, violent events seem to be more strongly related to lower mental health, perhaps due to trauma. This finding suggests that although the consequences of violence are not reflected in our measures of economic well-being, they are affected by mental health. Therefore, different types of victimization have different types of consequences on well-being. The findings on mental health are in line with Jamison et al. (2018), who also document a correlation between depressive symptoms and lower labor market participation and educational investment. Additionally, we find that both insurgent attacks as well as attacks by bandits and criminals are related to lower mental health at the 1 percent level of significance, but attacks by nomads are not. This result is similar with the results of the economic outcomes, where these perpetrators were most detrimental.

5.3.3. Poverty transitions

In terms of poverty, we are interested in investigating whether poor households are more likely to stay in poverty after having experienced conflict events and, conversely, whether nonpoor households are more likely to fall to poverty after having experienced conflict. Thus, we are interested in finding whether conflict events contribute to a change in a household's poverty status. We address this question by estimating models of the following form:

$$Poor_{i,l,t,w \mid non-poor_{i,,l,t,w=1}} = \alpha + \beta \sum_{j=w-1}^{t-1} Conflict_{i,j} + \boldsymbol{\gamma X}_{i,l,t,w} + \lambda_l + \theta_w + \varepsilon_{i,l,t,w} \qquad (2)$$

and

$$Nonpoor_{i,l,t,w \mid poor_{i,l,t,w=1}} = \alpha + \beta \sum_{j=w-1}^{t-1} Conflict_{i,j} + \boldsymbol{\gamma X}_{i,l,t,w} + \lambda_l + \theta_w + \varepsilon_{i,l,t,w} \qquad (3)$$

We therefore split the sample across the poverty status in wave one ($w = 1$). The variable $Poor_{i,l,t,w \mid non-poor_{i,,l,t,w=1}}$ takes the value 1 if a household i in the LGA l that was nonpoor in wave 1 switched to becoming poor in either of the subsequent waves and 0 if the household stayed nonpoor. Similarly, the variable $Nonpoor_{i,l,t,w \mid poor_{i,l,t,w=1}}$ takes the value 1 if a household that was poor in wave 1 became nonpoor 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. We use a linear probability model to estimate the specifications above. As previously stated, we cluster the standard errors at the LGA level.

Table C.2 displays transition probabilities in and out of poverty across all three waves. The variable of interest takes the value 1 if a household is poor in any given wave and the value 0 if the household is nonpoor. The poverty line used follows the international poverty line of US$1.90 per person per day (in 2011 PPP) (World Bank 2019), using the consumption aggregate.[26] This is also the poverty line used by the Nigerian government. We can see that there is strong persistence in being nonpoor: households that are nonpoor in wave 1 have an 83.7 percent probability of staying nonpoor during wave 2 and a 79.9 percent probability of staying nonpoor between waves 1 and 3. More variation exists among the initially poor: between wave 1 and 2, the probability of staying poor across the waves is 44.9 percent. Between waves 2 and 3, the persistence in poverty is higher at 59.6 percent.

Table 8 displays the results from estimating equations 2 and 3. Panel a shows the results of all conflicts and by each type of event, and panel b shows the results disaggregated by the type of perpetrator. Columns 1–3 display the model that uses the dummy for moving out of poverty (equation 3), and columns 4–6 display the model that has moved into poverty as the dependent variable (equation 2). Looking at columns 1–3 in panel a, we can see that households that have experienced conflict are marginally more likely to stay poor. Hence, conflict decreases the likelihood of moving out of poverty by 4 percent, and the result is significant at the 10 percent level. The results are stronger for the events related to violence (column 3) than for those related to property (column 2). A violent conflict event is associated with a decrease in the probability of becoming nonpoor by around 12.9 percent, a result that is significant at the 1 percent level.

[26] The last official poverty estimate in Nigeria is from 2009. The international poverty line of US$1.90 per day (2011 PPP) corresponds to 133.5 naira per person per day in 2009 prices.

This finding differs slightly from the consumption finding, in which property-related events were more strongly associated with a decrease in consumption over time. In table 8, we are only looking at the transition in the poverty status, and the relationship between violent events and consumption is significant for only those households that are poor. Therefore, being exposed to a violent event contributes negatively to their propensity to graduate out of poverty. In the results where the dependent variable is the log consumption, we are not estimating the effects at the poverty line; instead, we use variation in the entire consumption distribution. It does, therefore, seem that different types of events have differential effects depending on which part of the consumption distribution is in question.

Columns 4–6 show results for estimating equation 2, the relationship between conflict exposure and becoming poor in rounds 2 or 3. We do not find that the exposure of any of the types of conflict events studied is related to a higher probability of falling into poverty for the sample of households that were nonpoor in wave 1. The coefficient estimates are all close to zero and are statistically insignificant.

This evidence suggests that the burden of conflict disproportionately affects the households that were poor in wave 1, as compared to households that were nonpoor in wave 1. Nonpoor households are able to cope such that they do not fall into poverty as a consequence of the conflict events, whereas the poor households are more likely to stay in a poverty trap as a consequence of a conflict event.

We find once more that when insurgents are the reported perpetrators, the effects are stronger, which is consistent with the results on consumption. Column 1 in panel b shows that conflict decreases the likelihood of moving out of poverty by 5.7 percent, an estimate that is significant at the 5 percent level.

In Mexico, a low-violence setting, Martínez-Cruz and Rodríguez-Castelán (2016) find similar results at the municipality level: violent crime is preventing poor municipalities from graduating out of poverty. In the case of the Burundi civil war, Mercier, Ngenzebuke, and Verwimp (2016) find stronger results: both poor and nonpoor households are affected at the initial stages of conflict. The difference in their findings, as compared to ours, could be due to the different nature of conflict. Perhaps a civil war with high-intensity violence levels is more likely to affect the entire distribution, whereas the Boko Haram insurgency or lower-intensity conflict in other regions are not affecting the population equally.

5.3.4. Regional heterogeneity

Next, we run models to test whether the effect of conflict events on our main outcome variables of interest—food insecurity and consumption—vary across the different geopolitical zones. We have reason to believe this could be the case because the nature and intensity of conflict varies across the three zones.

In table 9, the zone indicator is interacted with the conflict event variables. We can see that the effect of conflict on consumption is driven by the North East (column 5). We also find that the relationship between conflict events and food insecurity is strongest again in the North East (column 2), and it is also statistically significant at the 5 percent level in the North Central (column 1).

5.4. Robustness checks

5.4.1. 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 C, table C.3. We can see that the results are statistically significant at the 5 percent or 1 percent level, depending on the specification, and they are similar to those in table 2. The results on the additional item separately (columns 5 and 6) are also statistically significant.

5.4.2. Alternative samples on food insecurity

A second telephone survey round focusing on food insecurity was conducted between August 15 and September 8, 2017. During this second round, 581 of the 717 households in the conflict telephone survey were reinterviewed (only the 717 were attempted to be reached).[27] Due to the attrition, we present the results using this sample as additional results instead of as part of our main analysis. However, because the additional survey round was collected in autumn 2017, this sample allows us to employ the conflict information from 2016 and spring 2017 in the analysis, which provides an interesting robustness check.

[27] The attrition rates from the first to the second telephone survey rounds are 16 percent, 21 percent, and 19 percent for the North East, the North Central, and the South South, respectively. The geographical distribution of this sample is the following: 147 households in the North East, 219 in the North Central, and 216 in the South South.

The attrition between the two telephone survey rounds was mostly due to not being able to reach the respondents, possibly because of nonfunctioning phone numbers. Only 3 percent of respondents refused to answer the food insecurity telephone survey. To adjust for this attrition, weights were designed for this sample specifically, which we use in all of our estimations. In addition to accounting for the sampling and nonresponse issues in the conflict telephone survey, they also adjust for the attrition noted in the food security telephone survey.

The results are presented in appendix C, table C.4, and they can be considered as a robustness check for tables 2 and 3 (columns 1–3 in table C.4 correspond to columns 1–3 in table 2, and columns 4–8 in table C.4 correspond to columns 2, 4, 6, 8, and 10 in table 3). We can see that the results are similar with this smaller sample of households that extends to 2017. Table C.4 also confirms the finding that property-related events are more detrimental to food insecurity than are violent events, and that events perpetrated by insurgents as well as bandits and criminals are statistically significant. Magnitudes of the coefficient estimates are similar across the different specifications.

5.4.3. Unweighted results

In our main specifications, we have used sample weights to adjust for the oversampling of the conflict-affected LGAs as well as for the fact that not all targeted households were reached. To check for any biases the sampling strategy might have induced, we also run the same results without the weights.

The results are presented in appendix E, and they consistently show that they are robust to omitting the weights. Tables E.1 and E.2 present robustness checks for the results on food insecurity (tables 2 and 3) and consumption (tables 4 and 5), respectively. The results are similar across both magnitude and significance when weights are not used.

5.4.4. Alternative lag structure of conflict

In our main specification, the number of years—and therefore the time periods of conflict exposure—vary across different waves because the outcome variables used are not measured at even time intervals. This can be problematic because food insecurity and consumption are measured with the same recall period at each time point. Due to this discrepancy, we run a robustness check with a specification where the lag structure is uniform across the waves. This model takes the form

$$Y_{i,r,t,w} = \alpha_i + \beta Conflict_{i,t-1} + \gamma \boldsymbol{X}_{i,r,t,w} + \theta_w + \varepsilon_{i,r,t,w} \tag{4}$$

where conflict in $t-1$ denotes conflict events only during the previous year relative to the second year of each specific wave 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) and therefore are omitting some of the conflict events.[28] The timing is illustrated in appendix F, figures F.1 and F.2.

Tables F.1 and F.2 present robustness checks for the results on food insecurity (tables 2 and 3) and consumption (tables 4 and 5), respectively. We can see that the results are robust to this alternative lag structure. The effects are even slightly stronger for food insecurity, which is a more volatile measure of well-being than consumption, and violence also seems to matter in this case, a result arising clearly from such shorter-term dynamics. The stronger effects on food insecurity suggest that households might have already recovered from the events that occurred further in the past, and their effect on food insecurity in period t is diminishing over time, perhaps suggesting that there is recovery from the initial shock when it comes to food insecurity and violent events. There might be an initial drop in welfare, as we find in our robustness check, but over time the household might start recovering. Overall, our main results remain unchanged with the alternative lag structure.

6. Conclusions

In this paper, we have analyzed the relationship between victimization and household well-being by using panel data from Nigeria. We exploit the time and spatial variation of victimization to analyze these effects within a household fixed effects framework using up to six rounds of data. We find that victimization negatively affects household welfare, measured by consumption and food insecurity. We also find that property-related events are more detrimental to household welfare than are violent events. Both types of acts are perpetrated by different groups. Insurgents, bandits and criminals, and clashes between farmers and herders all involve both violence and property-related crimes. However, these different perpetrators might have different motivations for their acts, which might lead to different consequences for the household. Indeed, we find that consumption and food insecurity are

[28] For the analysis with the wave-based consumption aggregate measured in 2010–11, 2012–13, and 2015–16, we consider events that took place in 2010, 2012, and 2015. For the food insecurity analysis, the outcome variables are measured in 2011, 2012, 2013, 2015, and 2016. Therefore, we use conflict information from 2010, 2011, 2012, 2014, and 2015, and we are only dropping 2013 conflict events. As in the main analysis, here food insecurity in 2010 also is not part of the analysis as we do not have conflict data preceding that year.

affected by insurgent attacks, but food insecurity also increases as a consequence of events perpetrated by criminals. Results are strongest in the North East, where conflict exposure with the ongoing Boko Haram insurgency has been the highest of the three regions. Furthermore, we find evidence of a relationship between victimization and low mental health, such that violence seems to matter more than property-related events do. Our results are robust to several different model specifications, different sample specifications using additional food insecurity data, different measures of the CSI, and accounting for assistance. We contribute to the literature by highlighting the importance of gaining a nuanced understanding of victimization: understanding the perpetrators of the attacks is as important as understanding whether households were exposed to violence or property crimes.

The results on poverty transition show that conflict prevents poor households from graduating out of poverty. This result is particularly striking given the income distribution in Nigeria and its development during the 2000s. The size of the middle class in Nigeria is small, estimated at 20 percent in 2013 (Corral Rodas, Molini, and Oseni 2019). Whereas the share of the middle class has been declining in the northern regions, it has increased in the southern areas. Overall, there has been a strong polarization of consumption between the wealthier south and the poorer north (Clementi et al. 2017). Our poverty transition results are indeed suggestive of some polarization. Given that a large, well-off middle class is often associated with better functioning civil society and social stability, more research is needed to investigate the link between the shrinking middle class and the conflict in the north and how it relates to the wealth distribution changes at the country level. Furthermore, because some states in the North East have been more affected than others, data that is representative at the state level could better reveal the regional heterogeneity in the effects of victimization across the most conflict-affected states.

References

Adelaja, A., and J. George. 2019. "Effects of Conflict on Agriculture: Evidence from the Boko Haram Insurgency." *World Development* 117 (May): 184–95. https://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.* Durban, South Africa: African Centre for the Constructive Resolution of Disputes. https://www.accord.org.za/ajcr-issues/towards-ending-conflict-insecurity-niger-delta-region/.

Akresh, R., S. Bhalotra, M. Leone, and U.O. Osili. 2012. "War and Stature: Growing Up during the Nigerian Civil War." *American Economic Review*, *Papers and Proceedings* 102 (3): 273–77.

Akresh, R., S. Bhalotra, M. Leone, and U.O. Osili. 2017. "First and Second Generation Impacts of the Biafran War." NBER Working Paper 23721, National Bureau of Economic Research, Cambridge, MA. https://www.nber.org/papers/w23721.pdf.

Akresh, R., P. Verwimp, and T. Bundervoet. 2011. "Civil War, Crop Failure, and Child Stunting in Rwanda." *Economic Development and Cultural Change* 59 (4): 777–810.

Alloush, M. 2019. "Income, Psychological Well-Being, and the Dynamics of Poverty." Working Paper. https://mmalloush.files.wordpress.com/2019/01/malloush_jmp_jan2019.pdf.

Azad, A., E. Crawford, and H. Kaila. 2018. *Conflict and Violence in Nigeria: Results from the North East, North Central, and South South Zones*. Washington, DC: World Bank Group. 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. and H. Kaila. 2018. *Food Insecurity in Conflict Affected Regions in Nigeria: Results from the North East, North Central, and South South Zones*. Washington, DC: World Bank Group 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.

Barrett, C.B. 2010. "Measuring Food Insecurity." *Science* 327 (5967): 825–28. https://doi.org/10.1126/science.1182768.

Bertoni, E., M. Di Maio, V. Molini, and R. Nisticò. 2018. "Education Is forbidden: The Effect of the Boko Haram Conflict on Education in North-East Nigeria." *Journal of Development Economics*. https://doi.org/10.1016/j.jdeveco.2018.06.007.

Blattman, C., and J. Annan. 2010. "The Consequences of Child Soldiering." *Review of Economics and Statistics* 92 (4): 882–98.

Blattman, C., and E. Miguel. 2010. "Civil War." *Journal of Economic Literature* 48 (1): 3–57.

Brück, T., M. d'Errico, and R. Pietrelli. 2019. "The Effects of Violent Conflict on Household Resilience and Food Security: Evidence from the 2014 Gaza Conflict." *World Development* 119 (July): 203–23. https://doi.org/10.1016/j.worlddev.2018.05.008.

Bundervoet, T., P. Verwimp, and R. Akresh. 2009. "Health and Civil War in Rural Burundi." *Journal of Human Resources* 44 (2): 536–63.

Chamarbagwala, R., and H.E. Moran. 2011. "The Human Capital Consequences of Civil War: Evidence from Guatemala." *Journal of Development Economics* 94 (1): 41–61. https://doi.org/10.1016/j.jdeveco.2010.01.005.

Clementi, F., A.L. Dabalen, V. Molini, and F. Schettino. 2017. "When the Centre Cannot Hold: Patterns of Polarization in Nigeria," *Review of Income and Wealth* 63(4): 608–32. https://doi.org/10.1111/roiw.12212.

Corral Rodas, P.A., V. Molini, and G. Oseni. 2019. "No Condition Is Permanent: Middle Class in Nigeria in the Last Decade." *Journal of Development Studies* 55 (2): 294–310. https://doi.org/10.1080/00220388.2017.1366453.

Croke, K., A. Dabalen, G. Demombynes, M. Giugale, and J. Hoogeveen. 2012. "Collecting High Frequency Panel Data in Africa Using Mobile Phone Interviews." Policy Research Working Paper 6097, World Bank, Washington, DC.

Dabalen, A.L., and S. Paul. 2014. "Effect of Conflict on Dietary Diversity: Evidence from Côte d'Ivoire." *World Development* 58 (June): 143–58. https://doi.org/10.1016/j.worlddev.2014.01.010.

D'Souza, A., and D. Jolliffe. 2013. "Conflict, Food Price Shocks, and Food Insecurity: the Experience of Afghan Households." *Food Policy* 42 (October): 32–47. https://doi.org/10.1016/j.foodpol.2013.06.007.

Enamorado, T., L.F. López-Calva, C. Rodríguez-Castelán. 2014. "Crime and Growth Convergence: Evidence from Mexico." *Economics Letters* 125 (1): 9–13. https://doi.org/10.1016/j.econlet.2014.07.033.

Ichino, A., and R. Winter-Ebmer. 2004. "The Long-Run Educational Cost of World War II." *Journal of Labor Economics* 22 (1): 57–86. https://doi.org/10.1086/380403.

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

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

Jamison, J.C., K.R. McGee, G. Oseni, J.T.T. Perng, R. Sato, T. Tanaka, and R. Vakis. 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. http://documents.worldbank.org/curated/en/647701545257537283/The-Relationship-between-Conflicts-Economic-Shocks-and-Death-with-Depression-Economic-Activities-and-Human-Capital-Investment-in-Nigeria.

Justino, Patricia. 2012. "War and Poverty." In *The Oxford Handbook of the Economics of Peace and Conflict*, edited by M. R. Garfinkel and S. Skaperdas. New York: Oxford University Press.

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

Martínez-Cruz, A.L., and C. Rodríguez-Castelán. 2016. "Crime and Persistent Punishment: A Long-Run Perspective on the Links between Violence and Chronic Poverty in Mexico." Policy Research Working Paper 7706, World Bank, Washington, DC.

Martin-Shields, C.P., and W. Stojetz. 2019. "Food Security and Conflict: Empirical Challenges and Future Opportunities for Research and Policy Making on Food Security and Conflict." *World Development* 119 (July): 250–64. https://doi.org/10.1016/j.worlddev.2018.07.011.

Márquez-Padilla, F., F. Pérez-Arce, and C. Rodríguez-Castelán. 2015. "The (Non-) Effect of Violence on Education, Evidence from the 'War on Drugs' in Mexico." Policy Research Working Paper 7230, World Bank, Washington, DC. http://documents.worldbank.org/curated/en/226781467993518525/The-non-effect-of-violence-on-education-evidence-from-the-war-on-drugs-in-Mexico.

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

Mercier, M., R.L. Ngenzebuke, and P. Verwimp. 2016. "Violence Exposure and Welfare over Time: Evidence from the Burundi Civil War." Working Paper 198, Households in Conflict Network, Brighton, UK.

Minoiu, C., and O. Shemyakina. 2012. "Child Health and Conflict in Cote d'Ivoire." *American Economic Review Papers and Proceedings* 102 (3): 294–99.

Minoiu, C., and O.N. Shemyakina. 2014. "Armed Conflict, Household Victimization, and Child Health in Côte d'Ivoire." *Journal of Development Economics* 108 (May): 237–55. https://doi.org/10.1016/j.jdeveco.2014.03.003.

Monteiro, J., and R. Rocha. 2017. "Drug Battles and School Achievement: Evidence from Rio de Janeiro's Favelas." *Review of Economics and Statistics* 99 (2): 213–28. https://doi.org/10.1162/REST_a_00628.

NBS (National Bureau of Statistics). 2014. *LSMS-Integrated Surveys on Agriculture: General Household Survey, Panel 2012/2013*. Abuja: NBS and Federal Ministry of Agriculture and Rural Development; Washington, DC: World Bank.

https://siteresources.worldbank.org/INTLSMS/Resources/3358986-1233781970982/5800988-1282216357396/7337519-1388758418241/GHS_Panel_Survey_Report_Wave_2.pdf.

NBS. 2016. *LSMS-Integrated Surveys on Agriculture: General Household Survey, Panel 2015/2016.* Abuja: NBS and Federal Ministry of Agriculture and Rural Development; Washington, DC: World Bank. https://microdata.worldbank.org/index.php/catalog/2734/related-materials.

NBS and World Bank. 2016. *Basic Information Document: Nigeria General Household Survey, Panel 2015/16*. https://microdata.worldbank.org/index.php/catalog/2734/related-materials.

Nwankpa, M. 2014. "The Politics of Amnesty in Nigeria: A Comparative Analysis of the Boko Haram and Niger Delta Insurgencies." *Journal of Terrorism Research* 5 (1). http://doi.org/10.15664/jtr.830.

OCHA (United Nations Office for the Coordination of Humanitarian Affairs). 2017. *Nigeria: 2018 Humanitarian Needs Overview*. New York: OCHA. https://www.humanitarianresponse.info/sites/www.humanitarianresponse.info/files/documents/files/13022018_ocha_humanitarian_needs_overview.pdf.

Raleigh, C., A. Linke, H. Hegre, and J. Karlsen. 2010. "Introducing ACLED: An Armed Conflict Location and Event Dataset Special Data Feature." *Journal of Peace Research* 47 (5): 651–60. https://doi.org/10.1177/0022343310378914.

Rockmore, M. 2017. "The Cost of Fear: The Welfare Effect of the Risk of Violence in Northern Uganda." *World Bank Economic Review* 31 (3): 650–69. https://doi.org/10.1093/wber/lhw025.

Serneels, P., and M. Verpoorten. 2013. "The Impact of Armed Conflict on Economic Performance: Evidence from Rwanda." *Journal of Conflict Resolution* 59 (4): 555–92. https://doi.org/10.1177/0022002713515409.

Shemyakina, O. 2011. "The Effect of Armed Conflict on Accumulation of Schooling: Results from Tajikistan." *Journal of Development Economics* 95 (2): 186–200. https://doi.org/10.1016/j.jdeveco.2010.05.002.

Singhal, S. 2018. "Early Life Shocks and Mental Health: The Long-Term Effect of War in Vietnam." *Journal of Development Economics*. https://doi.org/10.1016/j.jdeveco.2018.06.002.

Swee, E.L. 2015. "On War Intensity and Schooling Attainment: The Case of Bosnia and Herzegovina." *European Journal of Political Economy* 40 (A): 158–72. https://doi.org/10.1016/j.ejpoleco.2015.08.001.

Verwimp, P. 2012. "Undernutrition, Subsequent Risk of Mortality and Civil War in Burundi." *Economics and Human Biology* 10 (3): 221–231. https://doi.org/10.1016/j.ehb.2011.09.007.

Verwimp, P., P. Justino, and T. Brück. 2018. "The Microeconomics of Violent Conflict." *Journal of Development Economics*. https://doi.org/10.1016/j.jdeveco.2018.10.005.

Weissman, M.M., D. Sholomskas, M. Pottenger, B.A. Prusoff, and B.Z. Locke. 1977. "Assessing Depressive Symptoms in Five Psychiatric Populations: A Validation Study." *American Journal of Epidemiology* 106 (3): 203–14. https://doi.org/10.1093/oxfordjournals.aje.a112455.

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

World Bank. 2019. *Poverty and Equity Brief: Sub-Sahara Africa, Nigeria, April 2019.* Washington, DC: World Bank. http://databank.worldbank.org/data/download/poverty/33EF03BB-9722-4AE2-ABC7-AA2972D68AFE/Global_POVEQ_NGA.pdf.

Tables

Table 1. Summary statistics by geopolitical zone

	Pooled		North East		North Central		South South	
	Mean	sd	Mean	sd	Mean	sd	Mean	sd
a. Wave-based sample								
Consumption (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
Nonfood 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
Conflict events	0.21	0.96	0.43	1.37	0.21	1.01	0.064	0.42
Conflict events violence	0.035	0.27	0.058	0.31	0.029	0.32	0.025	0.19
Conflict events property	0.089	0.43	0.15	0.52	0.12	0.54	0.021	0.18
Conflict events insurgents	0.10	0.68	0.35	1.27	0.026	0.28	0	0
Conflict events bandits/criminals	0.024	0.19	0.046	0.22	0.012	0.16	0.020	0.20
Conflict events 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
HH owns livestock	0.54	0.50	0.75	0.44	0.59	0.49	0.37	0.48
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 Strategies Index (CSI score)	2.87	5.54	1.79	3.86	2.40	5.37	3.94	6.33
Conflict events	0.13	0.69	0.26	0.97	0.13	0.74	0.039	0.32
Conflict events violence	0.021	0.20	0.035	0.22	0.018	0.25	0.015	0.14
Conflict events property	0.053	0.30	0.091	0.37	0.073	0.36	0.013	0.14
Conflict events insurgents	0.058	0.49	0.21	0.91	0.016	0.22	0	0
Conflict events bandits/criminals	0.014	0.14	0.028	0.16	0.0071	0.11	0.012	0.15
Conflict events pastoralists/nomads	0.034	0.39	0.0091	0.11	0.091	0.65	0.0015	0.054
Asset index	0.057	0.32	-0.027	0.35	0.050	0.29	0.12	0.31
HH owns livestock	0.57	0.50	0.77	0.42	0.61	0.49	0.41	0.49
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
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	

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

Table 2. The effect of victimization on food insecurity

	CSI				Rely on less preferred foods		Borrow or rely on help		Limit portion size		Restrict adult consumption		Reduce number of meals	
				Assistance=0										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Conflict events	0.052***	0.044**	0.046***	0.038**	0.058***	0.036*	0.012	0.025	0.055**	0.059**	0.056**	0.051**	0.060**	0.047**
	(0.019)	(0.018)	(0.015)	(0.016)	(0.016)	(0.019)	(0.020)	(0.020)	(0.027)	(0.024)	(0.025)	(0.023)	(0.028)	(0.018)
Observations	3,550	3,457	3,457	3,253	3,550	3,457	3,550	3,457	3,550	3,457	3,550	3,457	3,550	3,457
R-squared	0.013	0.029	0.040	0.040	0.005	0.027	0.015	0.054	0.021	0.038	0.005	0.028	0.008	0.030
Number of households	717	717	717	674	717	717	717	717	717	717	717	717	717	717
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
HH 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

Note: Dependent variable is the standardized CSI and the (standardized) components of that index. 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

Table 3. 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)
VARIABLES										
Property	0.104**	0.091***								
	(0.039)	(0.028)								
Violence			0.084*	0.061*						
			(0.047)	(0.036)						
Insurgents					0.074***	0.062***				
					(0.020)	(0.022)				
Bandits/criminals							0.253***	0.249***		
							(0.079)	(0.074)		
Pastoralists/nomads									-0.002	0.010
									(0.010)	(0.011)
Observations	3,550	3,457	3,550	3,457	3,550	3,457	3,550	3,457	3,550	3,457
R-squared	0.012	0.039	0.010	0.038	0.013	0.039	0.013	0.041	0.009	0.038
Number of households	717	717	717	717	717	717	717	717	717	717
Controls	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region-round FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Note: Dependent variable is the standardized CSI. Data used are 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: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 4. The effect of victimization on consumption

VARIABLES	Consumption (ln)				Nonfood (ln)		Food (ln)	
				Assistance=0				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conflict events	-0.035***	-0.038***	-0.032**	-0.023*	-0.047**	-0.042*	-0.028**	-0.026*
	(0.012)	(0.011)	(0.013)	(0.013)	(0.022)	(0.024)	(0.014)	(0.014)
Observations	2,125	2,075	2,075	1,953	2,125	2,075	2,125	2,075
R-squared	0.162	0.304	0.318	0.332	0.107	0.224	0.130	0.277
Number of households	717	717	717	674	717	717	717	717
Controls	NO	YES	YES	YES	NO	YES	NO	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES	YES	YES	YES
Region-wave FE	NO	NO	YES	YES	NO	YES	NO	YES

Note: Dependent variables are household log total consumption and consumption split into food and nonfood consumption. 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: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 5. The effect of victimization on consumption by event and perpetrator type

	Event type				Perpetrator type					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES										
Property	-0.087**	-0.066**								
	(0.037)	(0.032)								
Violence			-0.025	-0.034						
			(0.033)	(0.035)						
Insurgents					-0.040**	-0.049***				
					(0.020)	(0.016)				
Bandits/criminals							-0.068	-0.015		
							(0.073)	(0.071)		
Pastoralists/nomads									-0.039	-0.015
									(0.024)	(0.020)
Observations	2,125	2,075	2,125	2,075	2,125	2,075	2,125	2,075	2,125	2,075
R-squared	0.162	0.321	0.158	0.319	0.161	0.322	0.159	0.319	0.159	0.319
Number of households	717	717	717	717	717	717	717	717	717	717
Controls	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
HH FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region-round FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Note: Dependent variable is household log total consumption. 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: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 6. The effect of victimization on health and education expenditures by event type and perpetrator

VARIABLES	Health (ln)	Education (ln)	Health (ln)					Education (ln)				
			Event type		Perpetrator			Event type		Perpetrator		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Conflict events	-0.018	-0.173*										
	(0.098)	(0.090)										
Property			0.049					-0.550***				
			(0.243)					(0.199)				
Violence				0.082					-0.322			
				(0.239)					(0.336)			
Insurgents					-0.080					-0.137		
					(0.125)					(0.175)		
Bandits/criminals						-0.378					-0.471	
						(0.508)					(0.327)	
Pastoralists/nomads							0.215**					-0.126*
							(0.092)					(0.073)
Observations	2,075	2,075	2,075	2,075	2,075	2,075	2,075	2,075	2,075	2,075	2,075	2,075
R-squared	0.053	0.115	0.053	0.053	0.053	0.053	0.054	0.118	0.113	0.113	0.113	0.113
Number of households	717	717	717	717	717	717	717	717	717	717	717	717
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region-round FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Dependent variables are household (log) health and education expenditures. 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: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 7. Victimization and mental health by event type and perpetrator

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Conflict events	0.046**	0.046**										
	(0.023)	(0.019)										
Property			0.017	0.039								
			(0.063)	(0.055)								
Violence					0.169***	0.180***						
					(0.045)	(0.039)						
Insurgents							0.083***	0.077***				
							(0.022)	(0.026)				
Bandits/criminals									0.196**	0.283***		
									(0.081)	(0.068)		
Pastoralists/nomads											-0.036	-0.012
											(0.033)	(0.030)
Observations	717	643	717	643	717	643	717	643	717	643	717	643
R-squared	0.010	0.185	0.000	0.178	0.010	0.188	0.016	0.186	0.007	0.190	0.002	0.177
HH controls	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Geo controls	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Zone FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Note: Dependent variable is the log CES-D index collected in wave 3 of the GHS panel. Conflict variables are cumulative for the years 2010–16. All regressions are conducted using weights. Controls include all household and geographical variables listed in appendix table C.1. Household variables include controls for waves 1, 2, and 3, and geographical controls are for wave 3. Standard errors clustered at the local government area level.
Significance: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 8. Transitions in and out of poverty

VARIABLES	(1) Became nonpoor	(2) Became nonpoor	(3) Became nonpoor	(4) Became poor	(5) Became poor	(6) Became poor
a. Events by type						
Conflict events	-0.040*			-0.005		
	(0.020)			(0.009)		
Conflict events property		-0.070*			0.004	
		(0.039)			(0.033)	
Conflict events violence			-0.129***			0.004
			(0.048)			(0.024)
Observations	493	493	493	1,582	1,582	1,582
R-squared	0.548	0.547	0.547	0.350	0.350	0.350
Controls	YES	YES	YES	YES	YES	YES
LGA FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
b. Events by perpetrator						
Insurgents	-0.057**			-0.008		
	(0.027)			(0.013)		
Bandits/criminals		-0.029			-0.010	
		(0.076)			(0.037)	
Pastoralists/nomads			0.019			0.004
			(0.063)			(0.020)
Observations	493	493	493	1,582	1,582	1,582
R-squared	0.547	0.543	0.543	0.348	0.348	0.348
Controls	YES	YES	YES	YES	YES	YES
LGA FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: Dependent variables are the variables denoting becoming nonpoor after round 1 and becoming poor after round 1. 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 9. Regional heterogeneity: Main outcome variables

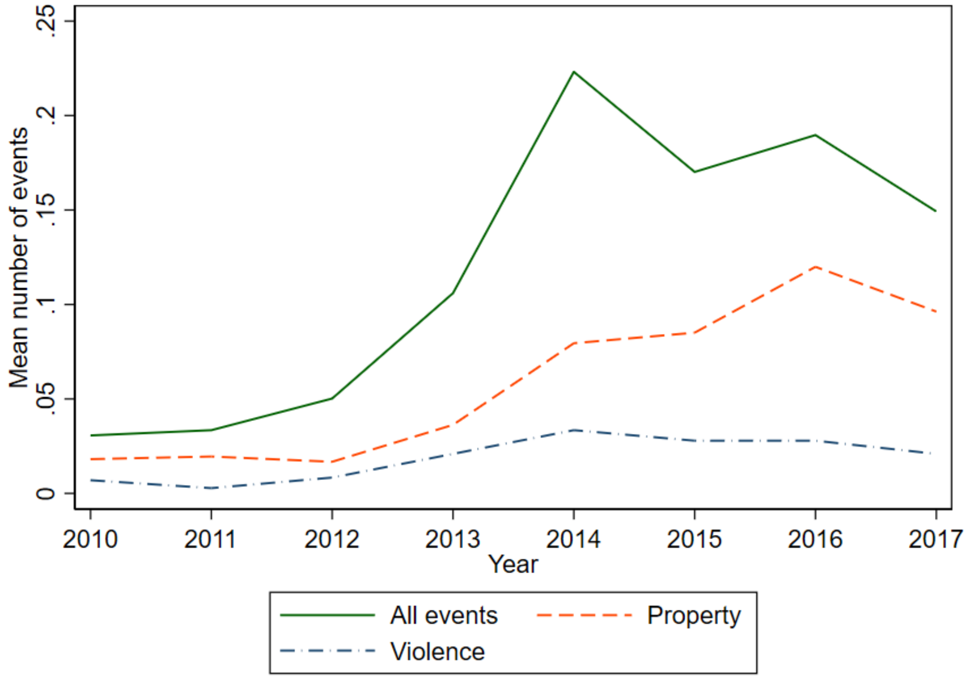
	Food insecurity			Consumption (log)		
VARIABLES	North Central	North East	South South	North Central	North East	South South
	(1)	(2)	(3)	(4)	(5)	(6)
Conflict events	0.0262**	0.0495**	0.0417	-0.025	-0.030*	-0.009
	(0.0120)	(0.0189)	(0.0349)	(0.024)	(0.016)	(0.039)
Observations	1,343	834	1,280	808	500	767
R-squared	0.045	0.125	0.050	0.279	0.240	0.465
Number of households	276	175	266	276	175	266
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
HH FE	YES	YES	YES	YES	YES	YES

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

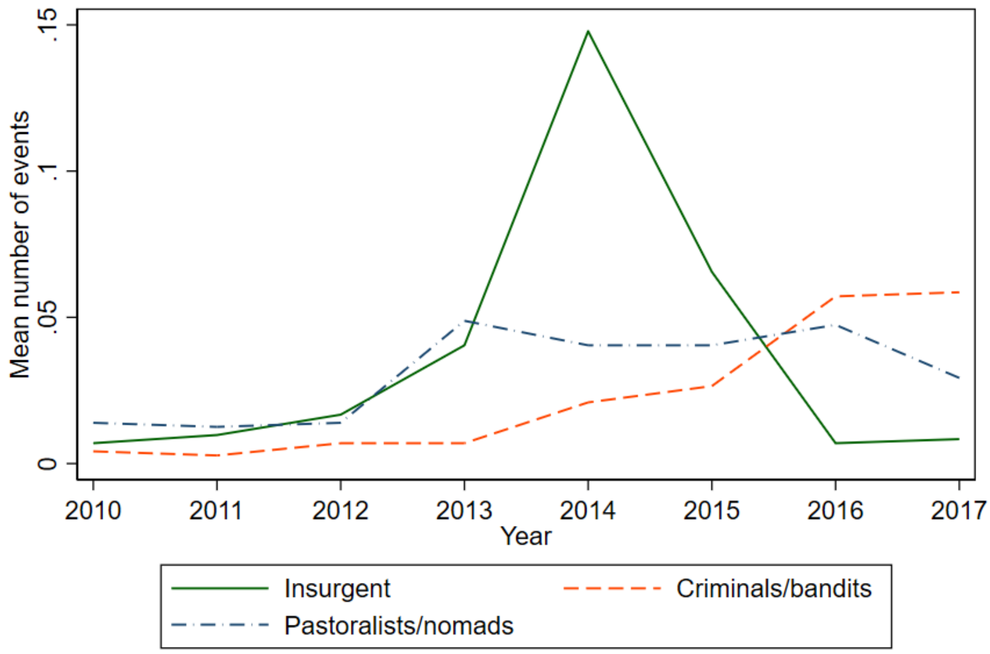
Figures

Figure 1. Mean number of events per household over time

a. By event type



b. By type of perpetrator

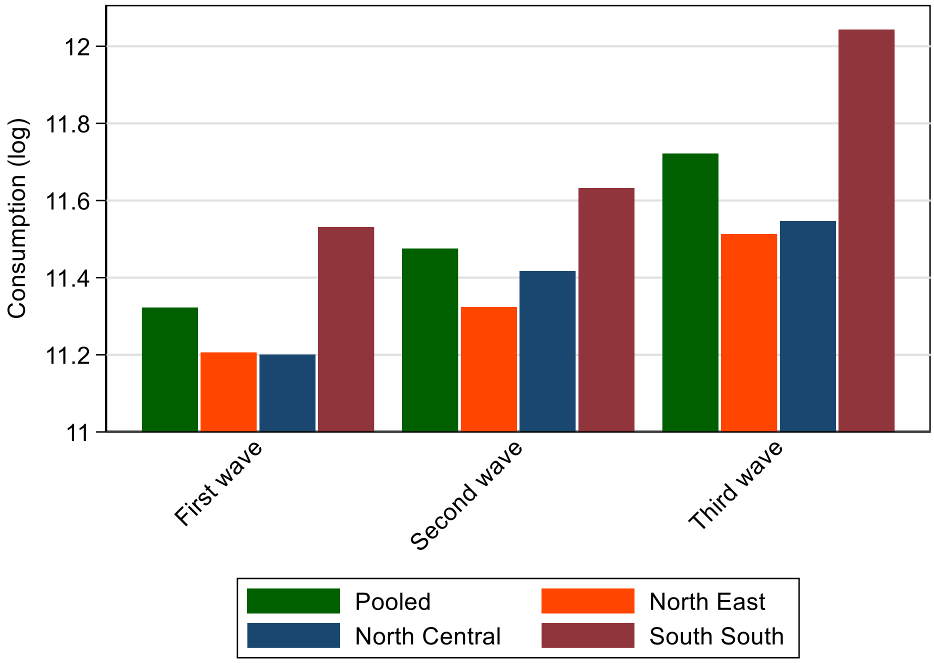


c.

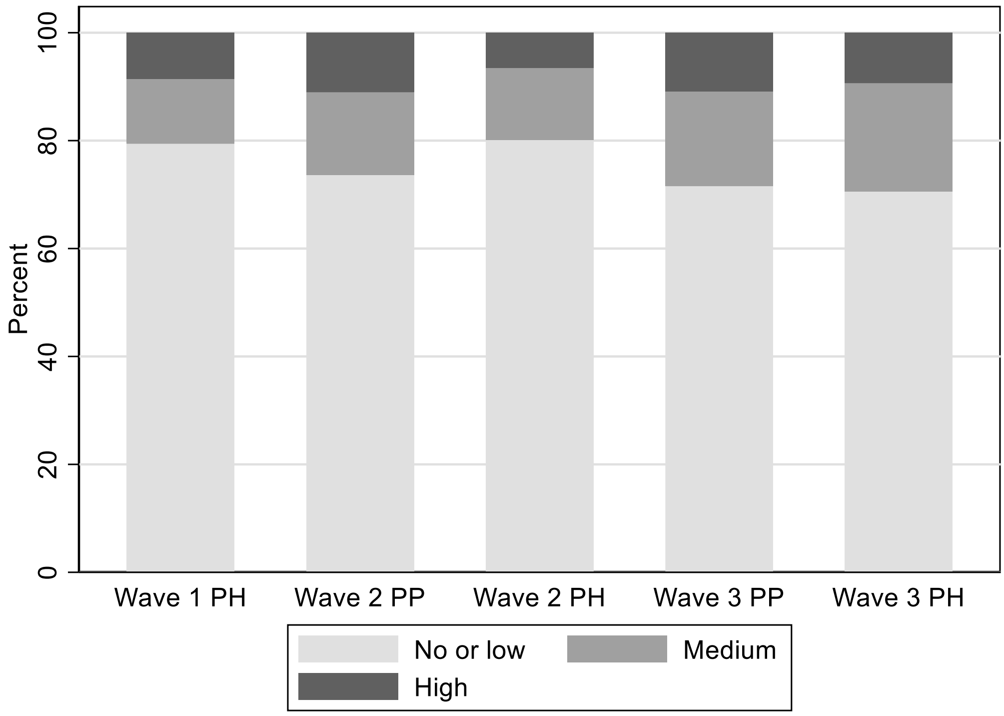
Note: The year 2017 only contains data until spring 2017.
Sources: Based on telephone survey data collected by the World Bank and the National Bureau of Statistics (NBS).

Figure 2. Outcome variables over time

a. Consumption across the three waves and three regions



b. Food insecurity over time



Note: "No or low" means CSI ≤ 3 (no food insecurity); "medium" means $3 < \text{CSI} \leq 9$ (medium food insecurity); and "high" denotes CSI > 9 (high food insecurity). Figures are plotted using weights
Sources: Based on GHS panel survey data collected by the World Bank and the National Bureau of Statistics (NBS).

Appendix A. Data

A.1. Questionnaires

A.1.1. Questions on conflict

An extract of the conflict questions administered in the telephone survey conducted in spring 2017 for 717 households in the GHS panel is shown below. For each reported event, questions about the timing and the perpetrator are asked for each year starting with 2010 and ending in 2017, as demonstrated below with 2010 and 2011 only.

1. Since 2010, has your household been affected by…?

Record YES/NO to each category:

1. Any household member killed (not natural death)
2. Any member suffered physical aggression (with or without any type of weapon)
3. Any member injured/disabled (after direct attack)
4. Any member suffered sexual violence
5. Any member forced to work (for free)
6. Any member captured/kidnapped/abducted
7. Any member robbed (money or assets)
8. Any member made a refugee/internally displaced
9. Household dwelling suffered from robbery
10. Household dwelling burned down/destroyed/seriously damaged/occupied
11. Household land occupied/expropriated/made unproductive
12. Household assets intentionally destroyed/seriously damaged
13. Household members restricted from going to or attending school
14. Household members restricted from seeking care at PHCs/clinics/hospitals[29]

2a. Did EVENT occur in **2010**?
2b. Who was the perpetrator of EVENT in **2010**?

1. Military
2. Police
3. Paramilitary
4. Militants
5. Insurgency
6. Bandits/Criminals
7. Pastoralist/Nomad
8. Neighbor(S)
9. Household Member(S)
10. Foreigner
11. Stranger
12. Vigilantes

[29] *PHC* refers to Primary Healthcare Center.

13. Other (specify)
2bOth. Please specify other perpetrator for **EVENT** in **2010**

3a. Did EVENT occur in **2011**?
3b. Who was the perpetrator of EVENT in **2011**?
3bOth. Please specify other perpetrator for **EVENT** in **2011**.

A.1.2. Consumption aggregate

The consumption aggregate is the per capita total household food and nonfood consumption expenditure collected in the household survey of both postplanting and postharvest visits during the three waves of the GHS survey. The wave-based consumption aggregate is the median consumption per capita of the two visits.

The consumption aggregate has been deflated using a monthly Consumer Price Index as well as adjusted with spatial variation in prices using prices derived from the survey. Details of the survey instruments are available from the NBS (NBS 2016) regarding the third wave. The reports and questionnaires can be downloaded from the World Bank Microdata Library (http://microdata.worldbank.org/index.php/catalog/2734).

A.1.3. Questions on food insecurity (CSI) from GHS data set

1. In the past seven days, how many days have you or someone in your household had to: (if no days, write "0")

    a. Rely on less preferred foods?
    b. Limit portion size at mealtimes?
    c. Borrow food or rely on help from a friend or relative?
    d. Reduce number of meals eaten in a day?
    e. Restrict consumption by adults in order for small children to eat?

A.1.4. Geographical control variables

The geographical control variables used in the analysis are obtained from the GHS data sets. The original sources of these variables vary. The LSMS team has merged these data with the GPS coordinates of the GHS households.

The details of the original sources of the variables can be found in the *Basic Information Document* (NBS and World Bank 2016).

Table A.1. Summary statistics by zone, geographical controls (three-wave panel)

	Pooled Mean	sd	North East Mean	sd	North Central Mean	sd	South South Mean	sd
Annual mean temperature (°C * 10)	262.3	11.5	262.5	8.98	259.8	17.4	264.3	3.26
Annual precipitation (mm)	1657.0	751.3	834.4	265.2	1324.2	130.7	2464.4	409.9
Slope (percent)	2.78	2.87	2.82	3.40	3.66	3.40	1.99	1.40
Elevation (m)	264.1	294.5	376.1	154.1	425.5	379.1	55.1	66.6
Potential wetness index	15.5	5.62	14.7	3.49	13.4	1.44	17.7	7.76
Terrain roughness	2.87	2.56	3.01	2.03	4.44	3.11	1.45	1.16
Average 12-month total rainfall (mm) for Jan.–Dec.	1375.9	428.8	929.4	336.5	1246.4	154.5	1770.4	261.7
Observations	2125		516		825		784	

Note: Description of the variables is given in table A.2. sd = standard deviation.

Table A.2. Description and source of geographical controls

Geovariables	Description or source
Annual mean temperature (°C * 10)	Average annual temperature calculated from monthly climatology, multiplied by 10 (°C) (University of California, Berkeley, WorldClim Bioclimatic Variables)
Annual precipitation (mm)	Total annual precipitation, from monthly climatology (mm) (University of California, Berkeley, WorldClim Bioclimatic Variables)
Slope (percent)	Derived from unprojected 90m SRTM using DEM Surface Tools
Elevation (m)	Elevation (m), aggregated to 1 km block
Potential wetness index	Downloaded from AfSIS website. Derived from modified 90 m SRTM. Local upslope contributing area and slope are combined to determine the potential wetness index: WI = ln (A s / tan(b)) where *A s* is flow accumulation or effective drainage area and *b* is slope gradient.
Terrain roughness	Derived from 90 m SRTM using 15 Meybeck relief classes and 5x5 pixel neighborhood (LSMS-ISA)
Average 12-month total rainfall (mm) for Jan.–Dec.	Average 12-month total rainfall (mm) for Jan.–Dec. (National Oceanic and Atmospheric Administration)

Note: Summary statistics of these variables are reported in table A.1.

A.2. Telephone survey sample

A total of 717 households were interviewed in the telephone survey. These were households that had been part of the GHS panel and had been interviewed in wave 3, visit 2.

All of the households had been residing in the same LGA during the time of the GHS survey; thus, no migration occurred among the households selected for the phone survey. Migration in general was low during the other waves: out of 4,916 households in wave 1, visit 1, for the entire country, only 142 households had moved by the end of wave 2, visit 2 (that is, 2.9 percent). The majority of the households that had moved were from the South West zone (Lagos and surrounding states), which is outside of our geographical sample. Within the three zones studied, only 52 households moved between wave 1, visit 1, and wave 2, visit 2. Between wave 2, visit 2, and wave 3, visit 2, another 212 households moved; tracking surveys were administered to these households in lieu of the regular survey procedures (NBS 2014, 2016). Because our sample consists of households that were part of the panel, we do not have any movers in the sample. However, given the low rates of migration in our survey areas, we do not consider this to be a major limitation for the study.

The attrition rates between the GHS waves 1 and 2 and waves 2 and 3 were 5.7 percent and 8.4 percent, respectively. Some attrition between wave 2 and wave 3 resulted from not being able to reach some areas: a total of 14 enumeration areas could not be visited in the states of Borno and Yobe during wave 3, leading to the loss of 139 households from the sample. Furthermore, some households dropped from the sample because they refused to be interviewed, they were untraceable, or all members had died (NBS 2014, 2016). Since we are conducting analysis based on households that were part of the GHS wave 3, our sample does not in and of itself have conflict-induced attrition. However, we remain wary of the fact that this conflict-induced attrition could have biased our sample selection in such a way that we are not capturing the households that were most severely affected by conflict in Borno and Yobe. This attrition would therefore induce our victimization figures to be downward biased.

Table A.3 lists the sample sizes in each wave, showing that a vast majority of the households had been visited in all three waves. In the telephone survey, a total of 1,030 households from the GHS wave 3, visit 2 were attempted to be reached. Most of the nonresponses came from nonfunctioning phone numbers, as only 2.7 percent refused to answer. The survey first attempted to reach only 742 households, of which 529 could be reached and interviewed. In order to increase the sample size to a level that was considered adequate for the survey, an additional 288 replacement households—also from the GHS panel wave 3, visit 2—were included in the sample. Out of these replacement households, 188 could be interviewed. Therefore, altogether 1,030 households were attempted to be reached, with a final sample size of 717 completed interviews (175 interviews in the North East, 276 in the North Central, and 266 in the South South).

Detailed information on the sample and data collection procedures of the telephone survey can be found in Azad, Crawford, and Kaila (2018).

Table A.3. Sample sizes

Sample size in three-wave panel

	First wave	Second wave	Third wave	Total
Number of households	700	708	717	2125

Sample size in wave-visit-based panel (per round)

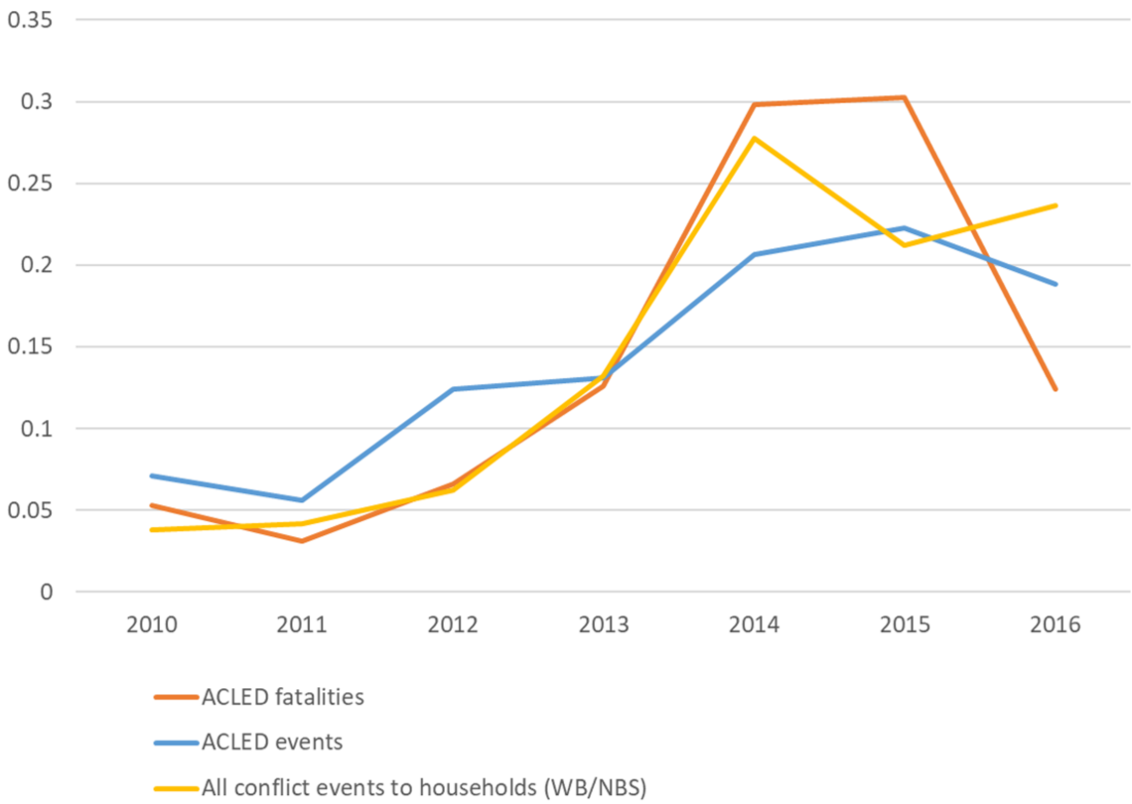
	Wave 1 PH	Wave 2 PP	Wave 2 PH	Wave 3 PP	Wave 3 PP	Total
Number of households	700	707	709	717	717	3550

Appendix B. Comparison to External Conflict Data

B.1. Time distributions

The conflict data is measured as a recall question in 2017, dating back to 2010. Therefore, we are wary of the possible bias in measuring such sensitive information. Events that have occurred further in the past might be harder to remember. To address the recall bias, we have compared the victimization data against an externally available data source, the ACLED database on fatalities and conflict events, which is frequently updated with information gathered from newspapers and similar external records. Figure B.1 displays the distribution of fatalities over time across the three different data sources for the North East, the North Central, and the South South. The y-axis thus denotes the share of deaths per year for each data set over the six-year period. For example, of all fatalities recorded in the ACLED database between 2010 and 2016, about 5 percent occurred in 2010. We are comparing the time intensity of the events instead of comparing the number of events because the number of events in the two data sets are not comparable.

Figure B.1. Intensity of conflict and victimization over time



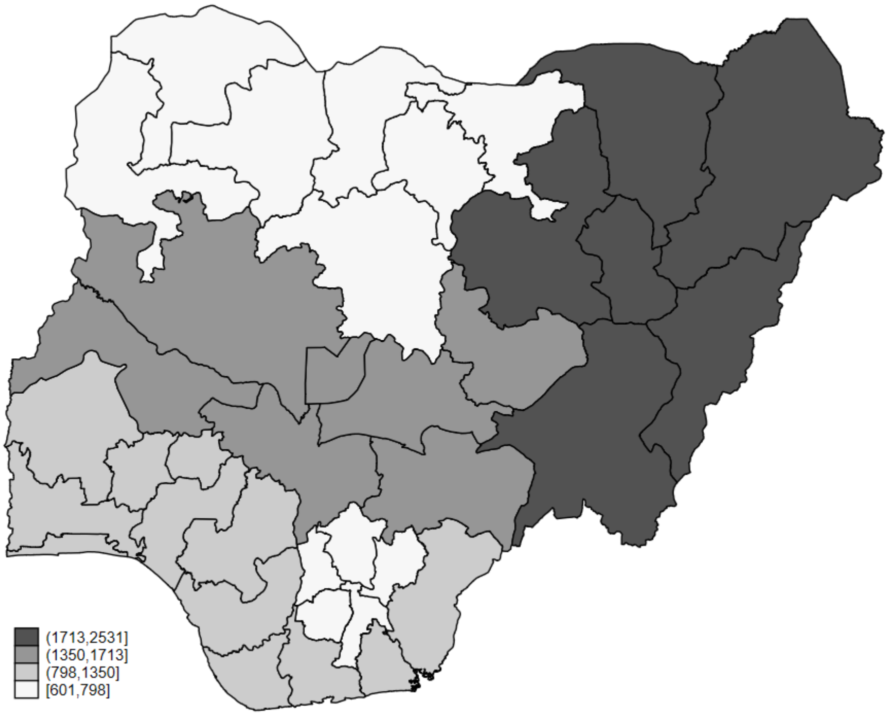
Note: The red and the blue lines denote the data for fatalities and events, respectively, as recorded in the ACLED database. The yellow line displays the data for all conflict events to households in the telephone survey as used in the analysis. The vertical axis denotes the share of events per year per data set spanning 2010–16.
Sources: Based on data from the Armed Conflict Location & Event Data Project (ACLED), World Bank (WB), and the National Bureau of Statistics (NBS).

B.2. Spatial distributions

The three regions in the telephone survey were chosen based on conflict intensity in a region as measured by ACLED. Figure B.2. panel a, illustrates the spatial distribution of events between January 2010 and May 2017. The North East has been hardest hit by conflict with a total of 2,531 events, followed by the North Central (1,713 events) and South South (1,350). In terms of fatalities, the North East and the North Central have the highest number of fatalities. However, the North West ranks third due to violent events taking place, mostly in the states of Kano and Kaduna, and the South South has the fourth-highest number of fatalities. However, given the recent increase in conflict in the South South, the South South was chosen for the telephone survey.[30]

Figure B.2. Conflict intensity across the six geopolitical zones in Nigeria

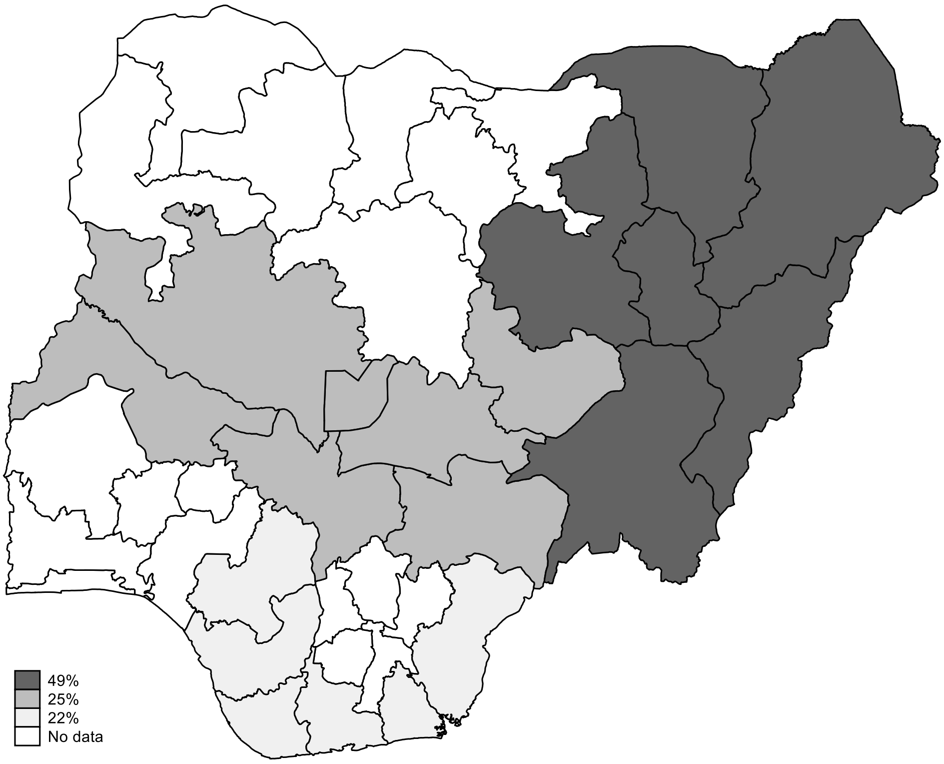
a. Number of conflict events in the six geopolitical zones of Nigeria



Note: The data shows the number of all events in the ACLED database in each geopolitical zone of Nigeria between January 2010 and May 2017.
Source: Based on data from the Armed Conflict Location & Event Data Project (ACLED).

[30] Since the GHS data is representative at the level of the geopolitical zone, the sample had to be drawn at that level as well. Thus, we could not choose individual states with the highest conflict exposure to be in the sample.

b. Household conflict exposure in the North East, the North Central, and the South South



Note: The figure illustrates that in the North East, 49 percent of households had experienced at least one conflict event between January 2010 and May 2017. In the North Central zone, the figure is 25 percent, and in the South South, 22 percent.
Source: Based on telephone survey conducted in the North East, the North Central, and the South South zones.

Appendix C. Additional Results

Table C.1. Mean comparison across household conflict exposure, first round

	No conflict	Conflict	Difference
a. Household characteristics			
Coping Strategies Index (CSI score)	2.48	2.05	0.43
Poverty status	0.24	0.24	-0.01
Consumption (ln)	11.32	11.32	0.01
Food consumption (ln)	10.93	10.92	0.00
Nonfood consumption (ln)	9.78	9.77	0.01
Health expenditures (ln)	2.95	3.29	-0.33
Education expenditures (ln)	5.91	6.10	-0.19
HH size	6.04	7.71	-1.67***
HH head male	0.87	0.89	-0.02
HH head age	47.99	47.29	0.70
HH head years of education	7.63	6.64	0.99*
Household lives in an urban area	0.34	0.31	0.03
HH head monogamous	0.63	0.56	0.06
HH head polygamous	0.19	0.29	-0.10**
HH head divorced, separated, or widowed	0.14	0.11	0.03
HH head employed	0.91	0.85	0.06*
Asset index	0.00	0.02	-0.01
HH owns livestock	0.42	0.53	-0.12**
b. Geographical characteristics			
Annual mean temperature (°C * 10)	263.76	257.69	6.07***
Annual precipitation (mm)	1696.27	1260.34	435.94***
Slope (percent)	3.23	2.95	0.27
Elevation (m)	235.57	398.19	-162.62***
Potential wetness index	14.55	15.24	-0.69
Terrain roughness	2.93	3.15	-0.21
Avg. 12-month total rainfall (mm) for Jan.–Dec.	1452.58	1174.47	278.12***

Note: Consumption, poverty, and the other variables include 553 households with no conflict events and 137 households with at least one conflict event. *First round* here indicates the second round for the CSI (the first round of analysis), the first wave of the three-wave panel used for the consumption and poverty analysis, variables on household characteristics as well as geographical variables. The asset index is constructed using factor analysis that includes 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. Summary statistics and a description of geographical variables are given in appendix A, tables A.1 and A.2, respectively.

Table C.2. Transition probabilities in poverty status

		Wave 2	
Wave 1		0	1
	0	83.71	16.29
	1	55.15	44.85
	Total	76.91	23.09
		Wave 3	
Wave 2		0	1
	0	82.82	17.18
	1	40.37	59.63
	Total	73.16	26.84
		Wave 3	
Wave 1		0	1
	0	79.89	20.11
	1	51.19	48.81
	Total	73	27

Note: Row and column "1" denote "poor" and "0" denote "nonpoor" in each wave. The numbers in the matrices denote transition probabilities related to moving from poor to nonpoor, vice versa, or staying poor or nonpoor from one wave to another.

Table C.3. Robustness check with alternative CSI (six items)

	CSI with six items				Limit the variety of foods	
				Assistance=0		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
Conflict events	0.057***	0.048**	0.051***	0.042**	0.072***	0.063**
	(0.020)	(0.019)	(0.016)	(0.018)	(0.022)	(0.025)
Observations	3,550	3,457	3,457	3,253	3,550	3,457
R-squared	0.013	0.029	0.040	0.040	0.011	0.040
Number of households	717	717	717	674	717	717
Controls	NO	YES	YES	YES	NO	YES
Year FE	YES	YES	NO	NO	NO	NO
HH FE	YES	YES	YES	YES	YES	YES
Region-round FE	NO	NO	YES	YES	NO	YES

Note: Dependent variable is the standardized CSI, including five items as listed in table 2, and an additional (standardized) component "Limit the variety of foods" included in the index. 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: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table C.4. Robustness check with additional telephone survey round

				Event type		Perpetrator type		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES								
Conflict events	0.071***	0.045**	0.052***					
	(0.026)	(0.020)	(0.016)					
Conflict events property				0.091***				
				(0.026)				
Conflict events violence					0.046			
					(0.038)			
Insurgents						0.081***		
						(0.020)		
Bandits/criminals							0.202**	
							(0.089)	
Pastoralists/nomads								0.018*
								(0.009)
Observations	3,458	2,802	2,802	2,802	2,802	2,802	2,802	2,802
R-squared	0.323	0.023	0.045	0.043	0.042	0.045	0.044	0.042
Number of households	581	581	581	581	581	581	581	581
Controls	NO	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	NO	NO	NO	NO	NO	NO
HH FE	YES	YES	YES	YES	YES	YES	YES	YES
Region-round FE	NO	NO	YES	YES	YES	YES	YES	YES

Note: Dependent variable is the standardized CSI. Data used are from the six visits of the GHS and telephone survey for conflict and an additional telephone survey with the CSI administered to 581 households in 2017. All regressions are conducted using weights specifically calibrated for the sample. 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

Appendix D. Data Collection Timeline

Figure D.1 illustrates the timeline of the data collection. It denotes the timing of the three rounds of the GHS with postplanting and postharvest visits in the autumn and spring, respectively, for each wave.

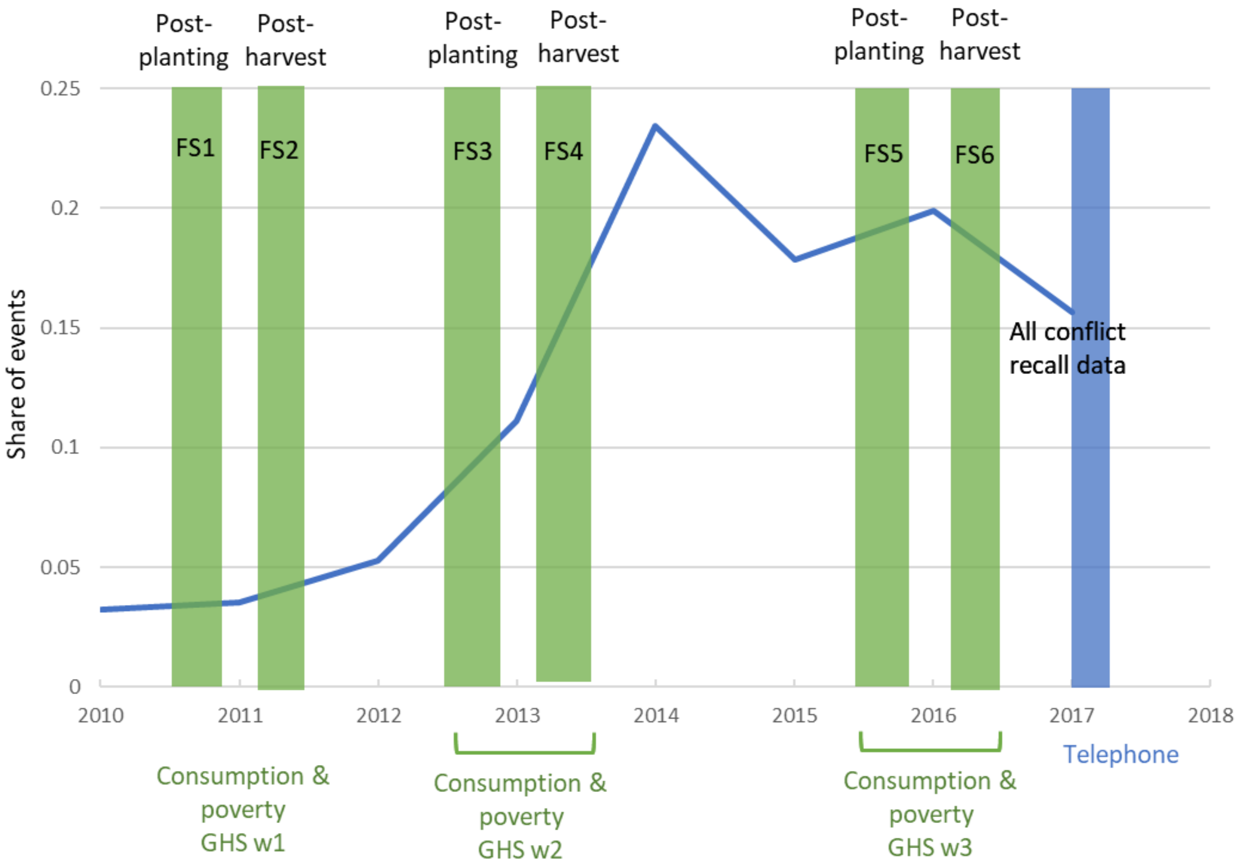
The telephone survey on conflict was conducted with 717 GHS households that were part of the GHS panel in wave 3, visit 2. It collected recall data on conflict events at the annual level from 2010 to 2016 and for spring 2017. The blue bar in the figure denotes the conflict intensity over time.

Figure D.2, panels a and b, show the merge of the outcome variables and the conflict recall periods for the consumption aggregate as well as food security, respectively. We have merged the outcome variables with the conflict data from the previous year; in cases where there is more than one year between two visits of the GHS, we have used data from several years.

For consumption, we have data from three waves that have two visits each. The consumption aggregate is the median of the consumption level of those two visits. Hence, we have a measure for consumption at three points in time. Conflict events that occurred *during or before each wave* are the main independent variable. The conflict events that took place before wave 1 (2010–11) are those that occurred in 2010; conflict events between wave 1 and wave 2 (2012–13) occurred in 2011 and 2012; and conflict events between wave 2 and wave 3 (2015–16) occurred in 2013, 2014, and 2015. Therefore, events that occurred in 2016–17 are dropped from the analysis because they have occurred mostly after the end of the last visit of data collection in spring 2016 (figure D.2, panel a).

For the food insecurity analysis, a six-round panel of the GHS, the first round (visit of wave 1, that is the postplanting visit in 2010) was excluded from the analysis because no conflict information existed for 2009. For the postharvest visit of the GHS (spring 2011), we include events in 2010. For the GHS wave 2, visit 1 (autumn 2012), events in 2011 were included; and for wave 2, visit 2 (spring 2013), events in 2012 were included. For autumn 2015, events in 2013 and 2014 were included; and for spring 2016, events in 2015 were included (figure D.2, panel b).

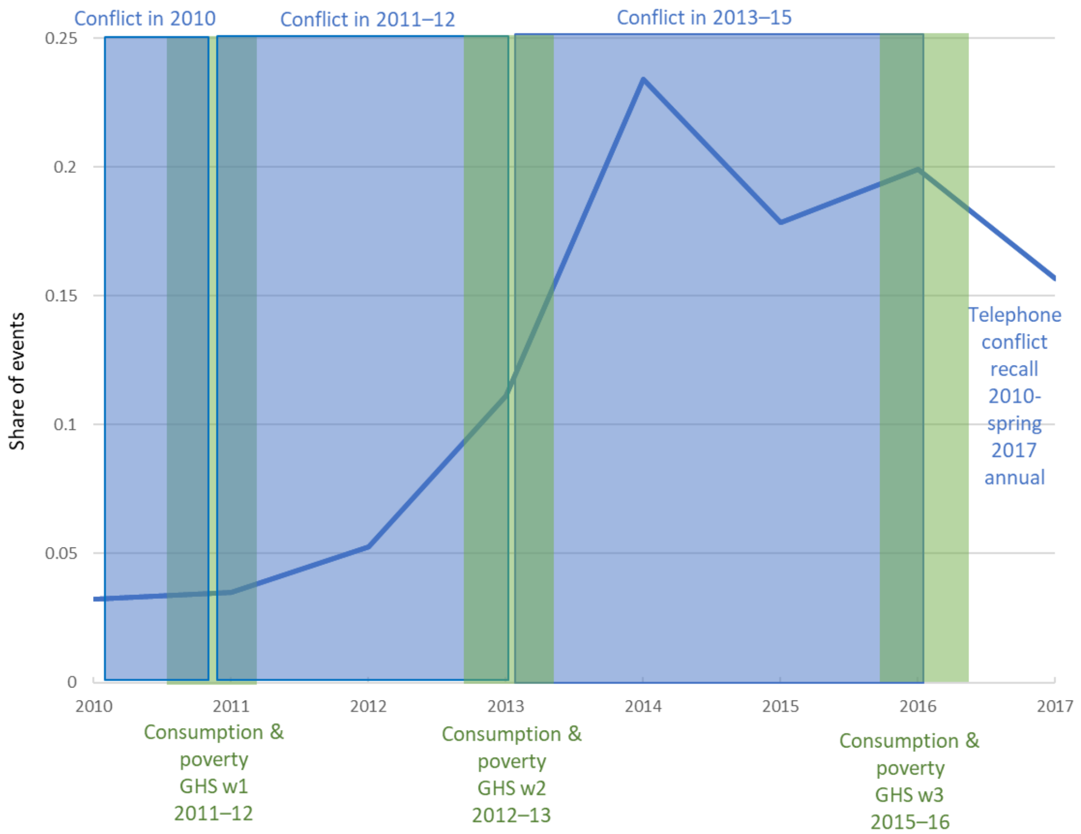
Figure D.1. Timeline of data collection



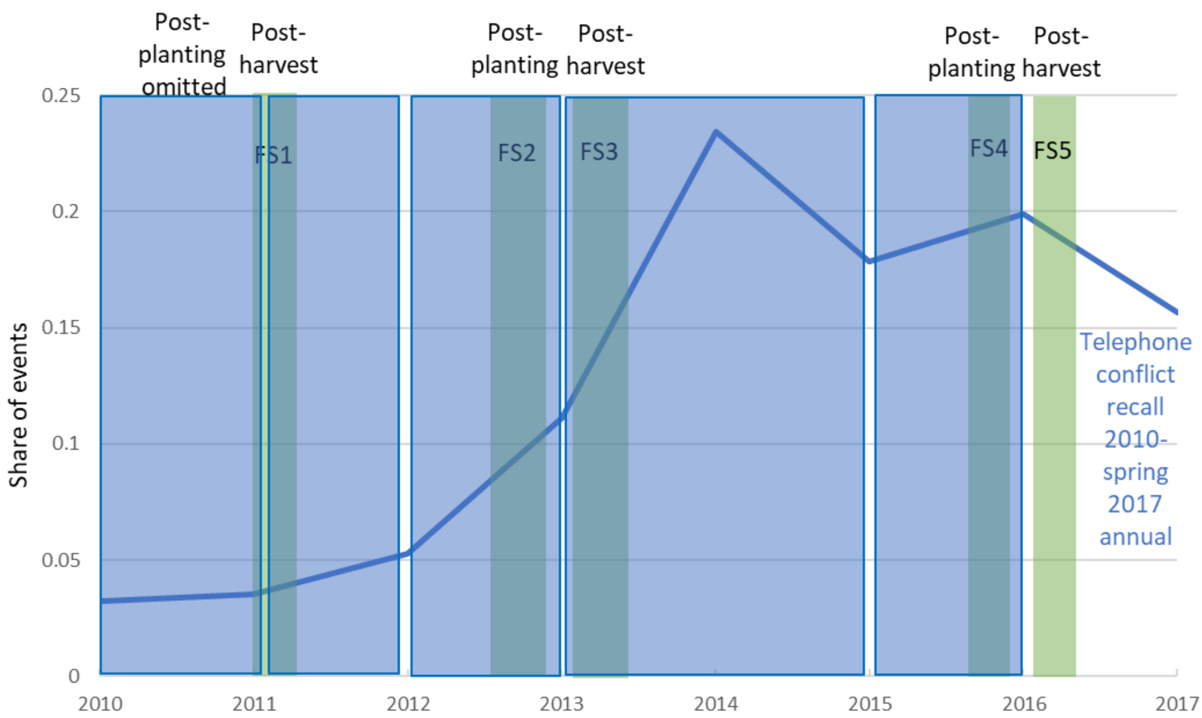
Note: Green bars denote the timing of each GHS panel visit in waves 1, 2, and 3. FS1–FS6 denote the timing of the collection of the CSI. The blue bar denotes the timing of the conflict telephone survey. The blue time-series line shows the annual time distribution of conflict events from 2010 to spring 2017, collected on annual recall in the telephone survey.

Figure D.2. Illustration of conflict recall period

a. Consumption as outcome variable and conflict recall period



b. Food insecurity as outcome variable and conflict recall period



Note: The green bars denote the time periods when the outcome variable data used in the analysis was collected (consumption and food insecurity). The blue bars denote the years of recall associated with the outcome variables. The conflict recall period illustrated corresponds to the main empirical specification of equation 1.

Appendix E. Unweighted Results

Table E.1. Conflict and food insecurity, unweighted regression

				Event type		Perpetrator type		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES								
Conflict events	0.052***	0.045***	0.045***					
	(0.017)	(0.017)	(0.015)					
Conflict events property				0.081***				
				(0.029)				
Conflict events violence					0.062*			
					(0.033)			
Insurgents						0.051**		
						(0.023)		
Bandits/criminals							0.247***	
							(0.080)	
Pastoralists/nomads								0.006
								(0.016)
Observations	3,550	3,457	3,457	3,457	3,457	3,457	3,457	3,457
R-squared	0.015	0.025	0.033	0.032	0.031	0.032	0.034	0.031
Number of households	717	717	717	717	717	717	717	717
Controls	NO	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	NO	NO	NO	NO	NO	NO
HH FE	YES	YES	YES	YES	YES	YES	YES	YES
Region-round FE	NO	NO	YES	YES	YES	YES	YES	YES

Note: Dependent variable is the standardized CSI. Data used are from the six visits of the GHS and telephone survey for conflict. No weights are used in any of the regressions. 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 E.2. Conflict and consumption, unweighted regression

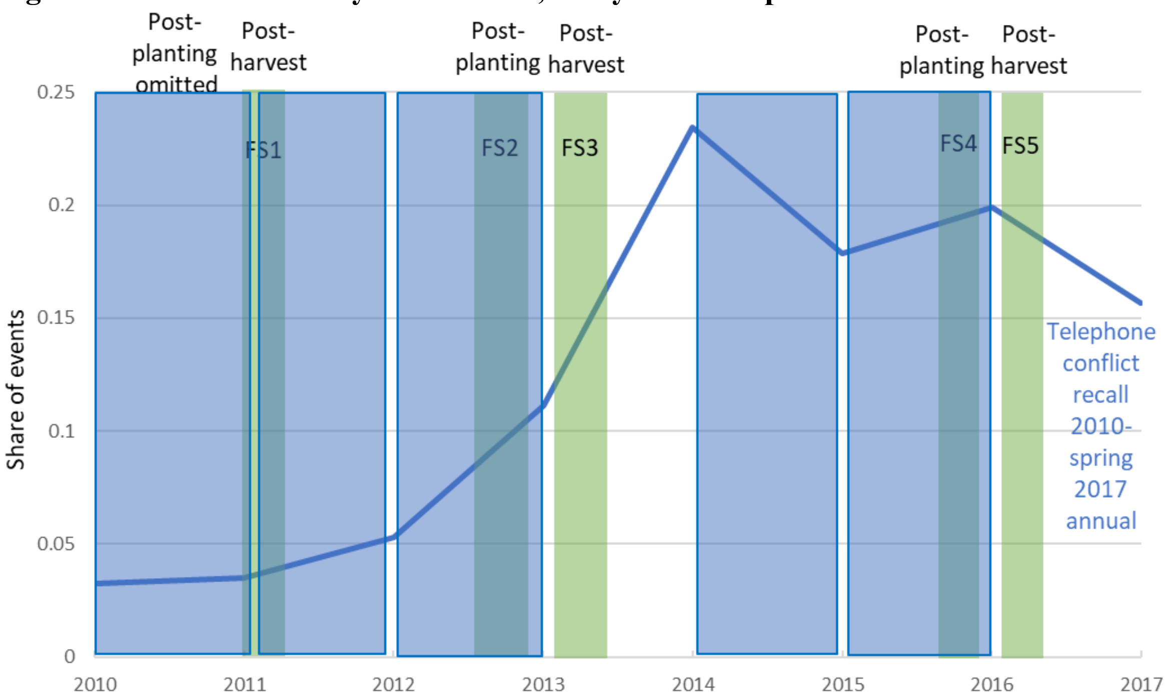
				Event type		Perpetrator type		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES								
Conflict events	-0.035***	-0.030***	-0.028**					
	(0.010)	(0.011)	(0.012)					
Conflict events property				-0.063**				
				(0.029)				
Conflict events violence					-0.005			
					(0.038)			
Insurgents						-0.041**		
						(0.016)		
Bandits/criminals							-0.050	
							(0.067)	
Pastoralists/nomads								-0.011
								(0.023)
Observations	2,125	2,075	2,075	2,075	2,075	2,075	2,075	2,075
R-squared	0.142	0.258	0.269	0.269	0.267	0.269	0.268	0.267
Number of households	717	717	717	717	717	717	717	717
Controls	NO	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	NO	NO	NO	NO	NO	NO
HH FE	YES	YES	YES	YES	YES	YES	YES	YES
Region-round FE	NO	NO	YES	YES	YES	YES	YES	YES

Note: Dependent variable is log consumption of household. Data used are from the three waves of the GHS and telephone survey for conflict. No weights are used in any of the regressions. Controls include all household and geographical variables listed in appendix table C.1. Standard errors clustered at the local government area level. Significance: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Appendix F. Alternative Lag Structure

Figure F.1. Consumption and conflict, one-year recall period

Figure F.2. Food insecurity and conflict, one-year recall period



Note: The green bars denote the time periods when the outcome variable data used in the analysis was collected (consumption and food insecurity). The blue bars denote the years of recall associated with the outcome variables. The conflict recall period illustrated corresponds to the main empirical specification of equation 1.

Table F.1. Conflict and food insecurity, alternative lag structure

				Event type		Perpetrator type		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES								
Conflict events	0.080***	0.071***	0.070***					
	(0.021)	(0.020)	(0.019)					
Conflict events property				0.126***				
				(0.036)				
Conflict events violence					0.119***			
					(0.042)			
Insurgents						0.080**		
						(0.032)		
Bandits/criminal							0.282***	
							(0.080)	
Pastoralists/nomads								0.021
								(0.019)
Observations	3,550	3,457	3,457	3,457	3,457	3,457	3,457	3,457
R-squared	0.014	0.031	0.041	0.040	0.038	0.040	0.041	0.038
Number of households	717	717	717	717	717	717	717	717
Controls	NO	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	NO	NO	NO	NO	NO	NO
HH FE	YES	YES	YES	YES	YES	YES	YES	YES
Region-round FE	NO	NO	YES	YES	YES	YES	YES	YES

Note: Dependent variable is the CSI. Data used are from the six visits of the GHS and telephone survey for conflict. The conflict recall is one year. 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 F.2. Conflict and consumption, alternative lag structure

				Event type		Perpetrator type		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES								
Conflict events	-0.082***	-0.051**	-0.046*					
	(0.020)	(0.023)	(0.024)					
Conflict events property				-0.142**				
				(0.056)				
Conflict events violence					-0.005			
					(0.084)			
Insurgents						-0.043		
						(0.028)		
Bandits/criminals							0.052	
							(0.103)	
Pastoralists/nomads								-0.193*
								(0.100)
Observations	2,125	2,084	2,084	2,084	2,084	2,084	2,084	2,084
R-squared	0.163	0.296	0.310	0.312	0.309	0.310	0.309	0.312
Number of households	717	717	717	717	717	717	717	717
Controls	NO	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	NO	NO	NO	NO	NO	NO
HH FE	YES	YES	YES	YES	YES	YES	YES	YES
Region-round FE	NO	NO	YES	YES	YES	YES	YES	YES

Note: Dependent variable is log consumption of household. Data used are from the three waves of the GHS and telephone survey for conflict. The conflict recall is one year. 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: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$