Essays on the impact of conflict on household welfare in Nigeria

by

Bolanle Atilola

B.S., Ladoke Akintola University of Technology, 2012
M.S., Kansas State University, 2018

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2024

Abstract

The farmer-herder conflict has escalated in Nigeria in recent years, causing detrimental impacts on agriculture, livelihoods, and human welfare. However, limited research exists on how this conflict affects children's health and nutrition in Nigeria. This dissertation aims to bridge the gap in the literature by estimating the causal impact of conflict on households' nutrition and health outcomes, as well as income. We assessed how the impact of conflict differs by conflict timing, geographical regions, and sub-population groups.

In the first chapter, we employ a difference-in-differences approach using data obtained from the 2018 Nigeria Demographic and Health Survey and Armed Conflict Location and Event Dataset to analyze the impact of farmer-herder conflict exposure on children's anthropometric outcomes. Our findings, while not showing a general impact of conflict exposure on children's anthropometric outcomes, reveal a significant and heterogeneous impact on children living in farm households when using a triple difference model.

Findings reveal that conflict significantly reduces weight-for-age and height-for-age Z-scores of exposed farm household children by 2.14 and 2.43 standard deviations, respectively, indicating increased underweight and stunting conditions. However, we find no statistically significant impact of conflict on weight-for-height Z-scores.

The second chapter analyzes the impact of farmer-herder conflict on crop income in Nigeria. Using panel data from the Nigeria General Household Survey (2010-2016) and geo-referenced conflict data, we implement a panel fixed effects model exploiting spatial and temporal variation in conflict events. Results reveal that exposure to conflict events within 10km does not have a statistically significant impact on crop income. This finding is robust at different

levels of conflict exposure. Further analysis shows no differential impact across different phases of the agricultural cycle.

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Major Professor
Dr. Timothy Dalton

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Chapter 1 - The impact of conflict on child's nutritional and health outcomes: The case of Farmer-Herder conflict in Nigeria

1.1. Introduction

Early childhood shock could have a devastating impact on children's nutritional and health outcomes (Akresh et al., 2011) and socioeconomic outcomes in adulthood (Akresh et al., 2017; Maccini & Yang, 2009). This impact could be exacerbated further through lingering effects if the shock affects the households' labor and physical assets (Mercier et al., 2016). Studies (Ghobarah et al., 2004; Gates et al., 2012; and Beyrer et al., 2007) have shown that conflict indirectly contributes to an increase in mortality rate by impeding the development, access, and resources available to the healthcare sector. Further, conflict promotes the development of chronic diseases and the spread of communicable diseases through internal displacement, disruption of the food supply chain, mental stress, gender-based violence, and destruction of social infrastructures.

Armed conflict exposure in early childhood could be especially debilitating because apart from the direct impact of the conflict exposure through the loss of household members and income and the psychological trauma associated with exposure to violence, an armed conflict event could indirectly threaten a child's well-being through food inaccessibility (George et al., 2020) and destruction of social infrastructures. For instance, Akresh et al. (2011) found that children exposed to conflict during early childhood are more likely to exhibit stunting, which may affect an individual's long-term economic productivity.

Farmer-Herder conflict is one of the major conflicts that has been ongoing in Nigeria over the last few decades (Raleigh et al., 2010). The conflict has received little attention due to its typically low-intensity nature (Moritz, 2010). Furthermore, other conflict events in Nigeria, like the Boko

Haram conflict in the northwest and the Niger Delta Avengers conflict in the southeast of Nigeria, have diminished attention to the Farmer-Herder conflict, leading to limited studies on its impact.

However, the frequency of Farmer-Herder conflict events has risen in recent years. In 2018 alone, the Farmer-Herder conflict accounted for almost 2000 fatalities, which is over 20 percent more fatalities compared to those related to the Boko Haram conflict in Nigeria (Matfess, 2018). Further, the drivers of the Farmer-Herder conflict in Nigeria, which include droughts (Madu & Nwankwo, 2020) and high population growth (ICG, 2018), are expected to increase over time (Shiru et al., 2020; United Nations, 2019). Hence, it is imperative to understand the impact of the conflict and the mechanisms through which it affects exposed households. This chapter aims to address this issue by evaluating the impact of Nigeria's Farmer-Herder conflict on children's nutritional and health outcomes.

This study makes three main contributions to the growing literature on violent conflict and food security. Firstly, to the best of our knowledge, this is the first study carried out to assess the causal impact of Farmer-Herder conflict on children's nutritional and health outcomes in Nigeria. This study utilized a fine-grained analysis to assess the impact of conflict on children's nutrition and health outcomes, specifically evaluating the effects on both short-term and long-term indicators such as weight-for-age, weight-for-height, and height-for-age Z-scores.

Secondly, the study used the DHS dataset, which provides information on households' clusters geo-coordinates in conjunction with the Armed Conflict Location and Event Dataset (ACLED), which contains information on the geo-coordinates of Farmer-Herder conflict locations to precisely identify conflict-exposed clusters using their distance to conflict locations. Further, due to the non-randomness of conflict events, this study employed multiple matching techniques to match conflict-exposed clusters to unexposed clusters based on cluster variables that may affect exposure to conflict and child's nutritional and health outcomes.

In this study, clusters are classified as conflict-exposed clusters if they are within a 10km radius of at least one Farmer-Herder conflict event between August 2017 and the time of the household survey in 2018. In addition, the study used 24-hour food recall information for children obtained from the DHS dataset. This allows for an analysis of conflict's impact on child nutrition and an investigation into whether dietary diversity serves as a pathway linking conflict to poor nutritional and health outcomes in children.

Lastly, the impact of conflict can vary depending on individual and household characteristics such as gender, level of education, residential location, and wealth status within the same population (Shemyakina, 2011; De Walque & Verwimp, 2010; Mercier et al., 2016). Moreover, Farmer-Herder conflict events primarily occur between herders and farmers in host communities, which suggests that farm households living in conflict-exposed clusters may experience a differential impact of conflict compared to non-farm households in the same clusters. Understanding the heterogeneous impacts of the Farmer-Herder conflict can help policymakers identify the most vulnerable groups, facilitating targeted interventions and efficient resource allocation.

This study uses cross-sectional data which was obtained from the Nigeria Demographic Health Survey (DHS) 2018 and the Armed Conflict Location and Event Data (ACLED) to evaluate the impact of Farmer-Herder conflict in Nigeria on children's anthropometric measures, which are weight-for-age Z scores (WAZ), weight-for-height Z scores (WHZ), and height-for-age Z scores (HAZ). Since conflicts do not occur haphazardly, their occurrence may be correlated to some of the factors affecting WAZ, WHZ, and HAZ scores, such as household socioeconomic status. Thus, we employed a caliper matching method to match households living in conflict-exposed and unexposed clusters based on observable variables that could affect household exposure to conflict and outcome variables (WAZ, WHZ, and HAZ scores) used in the study. We tested the mean difference between conflict-exposed and unexposed clusters after matching, and our findings show that households located in conflict-exposed clusters are not significantly different from households in unexposed clusters.

We used a difference-in-difference model, which exploits the spatial variation in the Farmer-Herder conflict event and the variation in conflict exposure across children's birth cohorts in this study. The model compares differences in anthropometric measures between children alive during conflict and children born after, across conflict-exposed versus unexposed clusters. Furthermore, we used a triple difference model to analyze the heterogeneous impact of conflict on children's anthropometric measures based on whether household heads or their spouses are engaged in an agricultural occupation.

Drawing on past studies on the impact of conflict on children's anthropometric measures and the anecdotal reports discussed in the literature review section on the impact of Farmer-Herder conflict in Nigeria, our first hypothesis is that conflict would have a negative impact on children's WAZ and WHZ scores. Since the Famer-Herder conflict events usually occur in agrarian communities and the primary actors are often farmers and herders, our second hypothesis is that the impact of conflict on WAZ and WHZ scores would be more profound for children living in farm households.

Lastly, fatalities and destruction of farm assets due to Farmer-Herder conflict in farming communities may cause loss of farm household members and income. Hence, farm households may experience a more severe conflict impact than non-farm households. Further, since the HAZ score is a measure of children's long-term nutritional and health outcomes, our third hypothesis is that conflict affects the HAZ scores of children from farm households but has no effect on children living in non-farm households.

The rest of this paper proceeds as follows. In the background section, the state of children's nutritional and health outcomes and the Farmer-Herder conflict in Nigeria are discussed. The ACLED and DHS datasets used in the study, as well as the spatial and temporal distribution of the Farmer-Herder conflict events, are discussed in the data section. Next, the empirical strategy used in the study is discussed, followed by a presentation of the results.

1.2. Background

Dietary diversity, undernourishment, wasting and stunting of children under five years of age in Nigeria.

Over the past decade, there has been a steady increase in malnutrition across the globe, and more than one in every ten people are severely food insecure in 2020 (FAO, 2021). Increasing food prices and income inequality were cited as the major factors driving inaccessibility to a healthy diet among 3 billion people in 2019 (FAO, 2021). About 12.6 % of the Nigerian population does not consume enough food to meet the minimum daily calorie requirement (World Bank, 2018).

A child's minimum dietary diversity (MDD) score, to a certain extent, reflects the nutritional sufficiency of a child's diet (FANTA, 2006; Kennedy et al., 2007; Mirminiam et al., 2004; Arimond et al., 2010). The MDD score is the count of selected food groups that the child is reported to have consumed in a 24-hour dietary recall (Kennedy et al., 2011). Using the WHO (2021) guidelines for Infant and Young Child Feeding (IYCF) practices, we constructed an MDD score comprising of 8 food groups for infants and young children between 6-23 months old. According to these guidelines, minimum dietary diversity is achieved if a child consumes at least five out of the eight food groups.

Another MDD score including 9 food groups was constructed for children between the age of 24-59 months old based on the FAO guidelines (Kennedy et al., 2011) for measuring individual dietary diversity score (IDDS). The FAO guidelines have no established threshold for the minimum number of food groups a child has to consume to meet minimum dietary diversity. However, Kennedy et al. (2007) found that a cut-off point between 5 to 6 food groups is ideal for achieving adequate micronutrient intake in non-breast-feeding children[1].

[1] The age of non-breast-feeding children in the study conducted by Kennedy et.al (2007) is between 24 to 71 months old.

Weight for age Z-score (WAZ), weight for height Z-score (WHZ), and height for age Z-score (HAZ) are anthropometric measures that represent children's short-term and long-term nutritional and health outcomes. The WHZ score is a measure of waste, and the HAZ score is a measure of stunting, which reflects acute and chronic undernutrition, respectively. The WAZ score is a measure of underweight, which reflects both acute and chronic undernutrition.

Some of the consequences of poor dietary intake include wasting and stunting, both often resulting from acute and chronic malnutrition, respectively. A child is considered to be wasted if her WHZ score is more than two standard deviations lower than the median weight-for-height of children between 0- 59 months of an international reference population. In addition, a child is said to be stunted if her HAZ score is more than two standard deviations lower than the median height-for-age of children between 0 - 59 months of an international reference population.

According to the World Bank (2018), between 4 - 14% of children living in sub-Saharan Africa are wasted. Comparatively, Nigeria has a lower percentage at 6.8% of under-five children wasted. Wasting can usually be rectified after a period of healthy dietary intake. However, stunting has irreversible consequences on a child's physical and mental ability in the long term if the condition is not corrected in the first 1000 days from conception (Roser & Ritchie, 2019). About 20 - 50 percent of children under five years of age living in sub-Saharan Africa are stunted; Nigeria is on the higher end of the spectrum, with 36.8% of its population of children under five years of age stunted (World Bank 2018). Inadequate nutritional intake and infection due to poor sanitary practices, among other factors, have been identified as some of the major causes of stunting and wasting in children under five years old.

The Farmer-Herder conflict in Nigeria

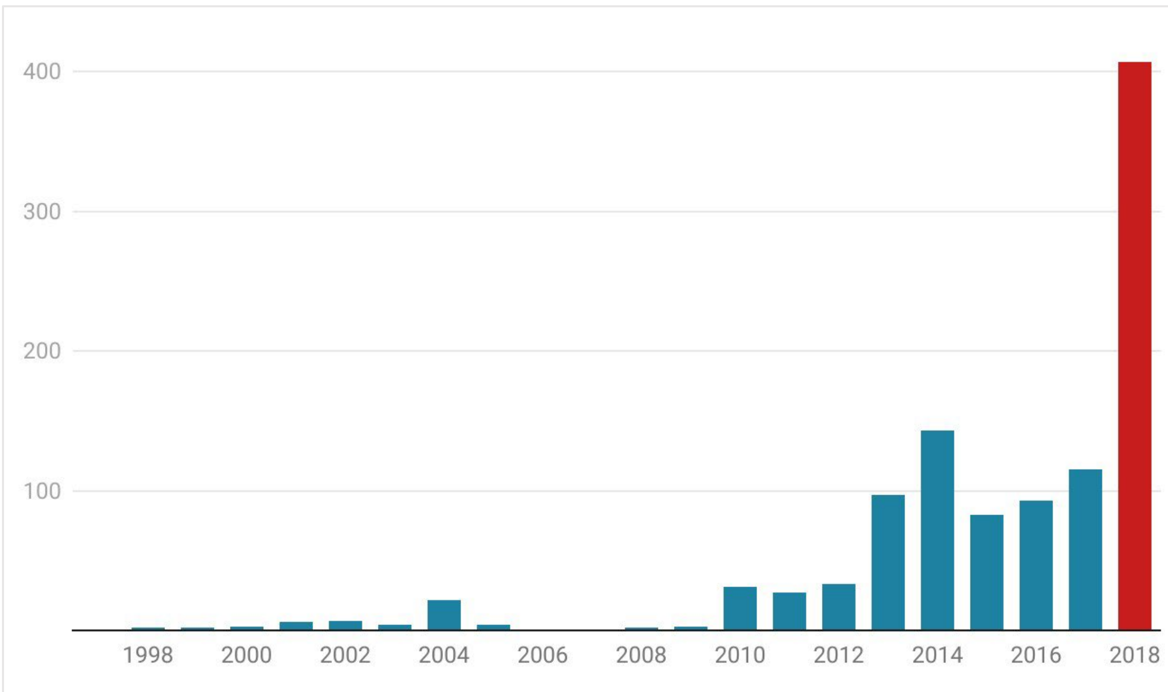
The Farmer-Herder conflict, as the name may suggest, is a conflict usually between herders of Fulani ethnic background and sedentary farmers from other ethnic groups. The conflict is primarily driven by increased competition for land resources, which is further exacerbated by local politics with an ethnic-religion aspect. Several factors contribute to the conflict, including encroachment on grazing corridors by sedentary farmers and the government due to population growth and urbanization (Benjaminsen, 2012). Land demands for residential, industrial, and agricultural purposes have led to an increase in the encroachment of grazing corridors (Peace, 2017).

Growing desertification, increasing temperatures, and longer periods of dry season due to climate change, rural banditry, and the Boko Haram conflict events in the northern part of the country have led to a significant reduction in pasture lands available to herders causing them to migrate farther south or relocate permanently to the central region of the country (PEACE, 2017). Boko Haram insurgents have been reported for poaching livestock from herders as well as occupying territories that were once grazing corridors for the herders.

In northern Nigeria, escalating cattle rustling by organized bandits has driven herders south, with major hotspots in forests across several states. The extent of cattle theft and violence, including the killing of thousands of herders and civilians, is significant but underreported due to limited security in remote areas. In 2013 alone, about 3000 herders were killed, and approximately 65,000 cattle were stolen in the north-central region of Nigeria (Peace, 2017). Vigilante groups formed to combat rural bandits have often worsened the situation by engaging in the extortion of herders for cash (Peace, 2017). In addition to migrating more frequently and to areas further south in the country, herders extend the length of the grazing period in host communities, which consequently facilitates tension and hostilities between the herders and the residents of the host communities (George et al., 2021).

The Farmer-Herder conflict is responsible for about 8000 reported fatalities over the last decade (Raleigh et al., 2010). About 400 Farmer-Herder conflict events were reported in 2018, which is over 300 percent of Farmer-Herder conflict events reported in any previous year, as shown in Figure 1.1. In the same year, Farmer-Herder conflict events are reported to have led to around 2000 fatalities in Nigeria, particularly in the north-central zone of the country (Raleigh et al., 2010).

Figure 1.1: Farmer-Herder conflict events (1997 -2018)

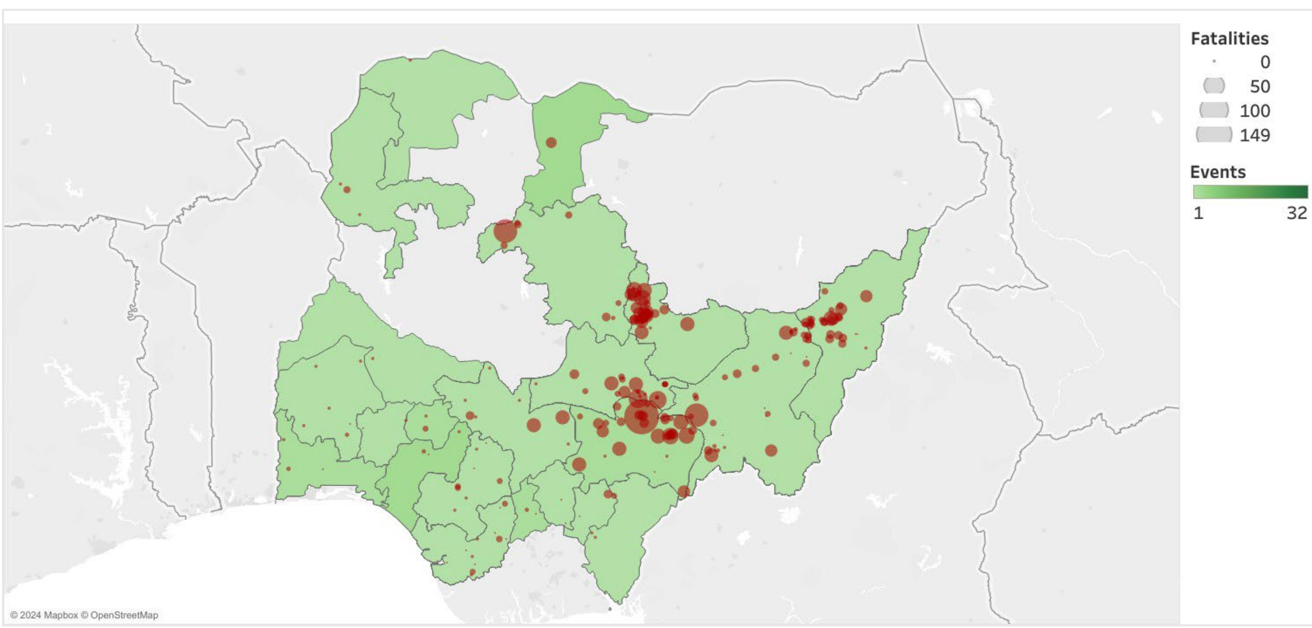


Source : ACLED (2023)

Figure 1.2 reveals the spatial distribution of Farmer-Herder conflict events and intensity between August 2017 and December 2018. Five states located in the north-central and northeastern regions of Nigeria account for about 80 percent of Farmer-Herder conflict events and 87 percent of conflict fatalities in 2018. This has resulted in a decline of agricultural productivity and increased rural poverty rates in the north-central region of the country.

The Farmer-Herder conflict led to about a 33 to 65 percent decline in agricultural production in three major food-producing states in the north-central region of Nigeria in 2018 (ICG, 2018). Further, because these states are often considered the food basket of the nation, conflict events could potentially lead to a countrywide increase in food prices and issues for agribusiness operations. At the national level, Mercy Corps (2015) estimated that in the absence of Farmer-Herder conflict in four states in the north-central region of Nigeria, revenue would increase by US$13.7 billion per annum, which is about 2.8 percent of Nigeria's GDP. The Farmer-Herder conflict has resulted in a significant amount of internal displacement, with an estimated 300,000 individuals affected (Nnoko-Mewama, 2018). Furthermore, the conflict has led to the destruction of approximately 7000 hectares of agricultural lands (Bukari, 2017).

Figure 1.2: Spatial distribution of Farmer-Herder conflict events and fatalities (2018)



Source: ACLED (2023)

1.3. Data and Description

To estimate the impact of the herder-farmer conflict on child nutrition and health outcomes, we use the Demographic Health Survey (DHS) 2018 data, which is nationally representative data from a survey conducted among Nigerian households from August 2018 to December 2018. The DHS dataset provides information on food consumption, birth date, height, and weight of children under five years, which are used in the construction of birth cohorts and outcome variables.

Furthermore, the DHS survey encompasses both farm[2] and non-farm households, allowing for a comparison of the impact of the Farmer-Herder conflict on both types of households. Households' residential location during the survey period might be different from the residential location during the conflict period (Akresh et al., 2012), hence, having information on household residence location during the period of conflict is essential to identify the households that are exposed[3] to conflict. The DHS dataset provides information on how many years a household has lived in the current residence, and using this information we can identify the households that lived in the current residence during the time of conflict.

We also use the ACLED data (Raleigh et al., 2010), which provides real-time information on conflict incidence, fatalities, actors as well as the geographic location of the conflict. Using geospatial information on household clusters obtained from the DHS dataset and conflict locations obtained from ACLED data (Raleigh et al., 2010), each conflict location was matched to clusters within a 10km radius of the conflict location using geodesic distance.

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[2] Farm households are households whose household heads or/and their spouses' occupation is in the agricultural sector.

[3] Households that are exposed to conflict in the study are household located in clusters within 10km radius of a conflict location from August 2017 and time of household interview in 2018.

Household clusters’ geospatial information reported in the DHS data is not entirely accurate due to geo-scrambling. This technique is used to protect respondents' confidentiality by randomly displacing clusters geographical location. Urban clusters are displaced by 2km, while rural clusters are displaced by 5km. In addition, one percent of the clusters in the DHS dataset are randomly displaced 10km away from their original location.

This random displacement may lead to measurement errors in studies that rely on this data. Specifically, it may result in inclusion errors if unexposed clusters are randomly displaced into the specified conflict exposure radius, or exclusion errors if exposed clusters are randomly displaced outside of the conflict exposure radius. Thus, misclassification of clusters as being either exposed or unexposed to conflict is possible. We employed two exclusion criteria to minimize this misclassification:

Exclusion of potentially misclassified conflict-exposed clusters: To account for the possibility that a cluster, originally within the conflict exposure radius, could be displaced outside the 10km buffer by geo-scrambling, we exclude urban and rural clusters that are farther than 8km and 5km from a conflict location, respectively. This approach acknowledges that an urban cluster displaced by a maximum of 2km, or a rural cluster by 5km, could erroneously be classified as unexposed. Therefore, in our analysis, conflict-exposed urban clusters are effectively at most 8km from a conflict location, and rural clusters are at most 5km away.

Exclusion of potentially misclassified unexposed clusters: To address the risk of incorrectly classifying unexposed clusters as exposed, we also exclude certain clusters based on their proximity to the conflict exposure radius. Urban unexposed clusters within 2km and rural unexposed clusters within 5km of the conflict exposure radius boundary are excluded. This precaution ensures that unexposed clusters, which could be erroneously displaced into the 10km radius due to geo-scrambling, are not mistakenly categorized as conflict-exposed clusters.

The spatial and temporal pattern of the 2017/2018 Farmer-Herder conflict events

The Farmer-Herder conflict has been ongoing for decades, historical data reveals a seasonal pattern to the event. The conflict usually peaks around January before gradually declining across the following months. Figure 1.3 reveals the temporal variation in Farmer-Herder conflict events in 2018. The Farmer-Herder conflict in January 2018 resulted in approximately 100 conflict events and 300 conflict fatalities before gradually declining to less than 10 conflict events in December. In general, the number of fatalities correlates with the number of conflict incidents.

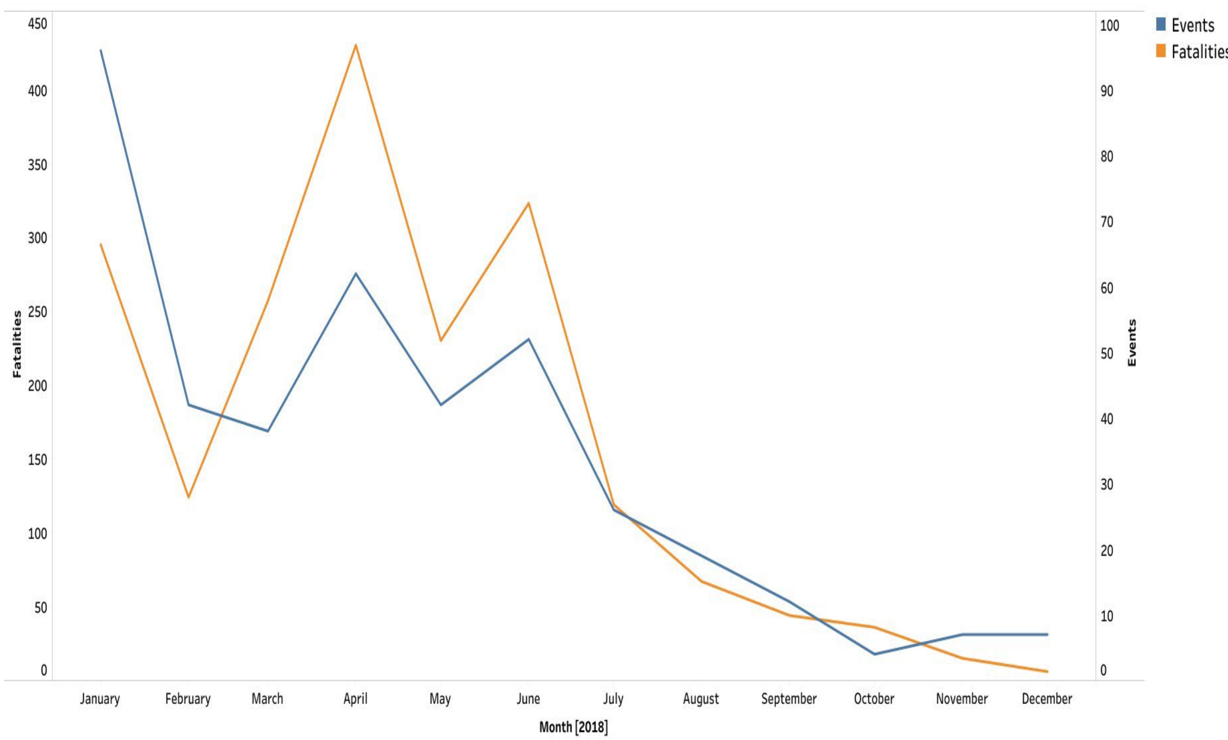
While all regions in Nigeria have experienced Farmer-Herder conflict at some point in time, the conflict is concentrated in the north-east and north-central regions of Nigeria as shown in Figure 1.2. The states of Benue and Plateau, which are located in the north-central region in conjunction with Nasarawa, Taraba, and Adamawa state, which are situated in the north-east region accounts for approximately 80% of the Farmer-Herder conflict incidents that occurred in 2018. As depicted in Figure 1.2, each of these states recorded over 40 conflict events in 2018. Further, these states in addition to Kaduna state, account for over 90 percent of all Farmer-Herder conflict fatalities in Nigeria in 2018, with over 100 fatalities in each state.

Farmer-Herder conflict escalated in 2018 after anti-open grazing laws were passed by states in the north-east and north-central region of the country in 2017. The anti-open grazing law bans the open grazing of cattle in the state in which they were enacted. Benue state passed an anti-open grazing law in May 2017 to be implemented in November 2017 (Kwaja and Ademola-Adelehin, 2017). Subsequently, Taraba state also passed an anti-open grazing law in July 2017 to be enacted in

February 2018, however, growing sentiments to pass such law in Plateau state were met with disapproval by the state government (Kwaja and Ademola-Adelehin, 2017).

Conflict events spiked prior to the enactment of the anti-open grazing laws. From September 2017 to October 2017, Farmer-Herder conflict events resulted in the displacement of about 13,726 people and 75 fatalities in Plateau state (Sesan, 2017). Further, Farmer-Herder conflict events from September 2017 and June 2018 led to approximately 1500 conflict fatalities and the displacement of 300,000 people (ICG, 2018). Within the same period, about 176,000 people were displaced in Benue, over 100,000 in Plateau, and approximately 19,000 in Taraba state (ICG, 2018).

Figure 1.3: Temporal variation in Farmer-Herder conflict events and fatalities (2018)



Source: ACLED (2023)

Conflict-exposed clusters and matched clusters

As discussed in the background section, one of the main reasons for the conflict escalation in 2018 is the anti-open grazing laws passed by Benue and Taraba state in May and July 2017, respectively. For this study, we are interested in how conflict events that occur after the passing of the anti-open grazing law affect children's anthropometric scores. Hence, we focus on the impact of conflict occurring from August 2017 to the time of survey in 2018.

Conflict-exposed clusters[4] are defined as clusters that are within a 10km radius of conflict locations while clusters that are outside the 10km radius are classified as unexposed clusters[5]. In exposed clusters, children are grouped into two birth cohorts based on whether they were born after the last conflict event in the cluster or alive when conflict occurred in the cluster. However, to account for conflict lingering effects, we included a 15-day period after the last conflict event in the cluster in defining birth cohorts. Hence, the birth cohort variable is assigned a value of "1" for children who were alive before and up to 15 days after the cluster's last conflict event, and "0" for children who were born at least 15 days after the last conflict event in the cluster. Conflict-exposed children are those who were alive before and up to 15 days after the cluster's last conflict event and living in conflict-exposed clusters at the time of survey.

This study's difference-in-difference framework relies on the hypothesis that in the absence of conflict, the difference in the WAZ, WHZ, and HAZ scores for children who are in the "alive during conflict" cohort living in conflict-exposed clusters, compared to children who are in the "born after

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[4] Excluding urban clusters that are beyond 8km and rural clusters that are beyond 5km of a conflict location.

[5] Unexposed urban and rural clusters are dropped if they are within 2km and 5km of the boundary, to prevent misclassification due to geo-scrambling.

conflict" cohort living in the same cluster would be similar to the difference between children in the two birth cohorts in matched unexposed clusters.

Table 1.1 presents the description of the dependent and independent variables used for analysis in this study along with their expected signs. The independent variable used in the analysis includes children and households' demographic and socio-economic characteristics. Table 1.2 reports the descriptive statistics of both the dependent and independent variables used in this study. The summary statistics in Table 1.2 comprise of observations used in the main estimation.

The second column of Table 1.2 reports the mean and standard deviation of each variable in the total sample. The mean and standard deviation of the variables in unexposed and conflict-exposed clusters are presented in the third and fourth column of the table, respectively. Further, the last column of the table reveals the difference between the mean of the variables in conflict-exposed and unexposed clusters.

Findings reveal that the mean values for WAZ, WHZ, and HAZ scores of children in the sample are negative, indicating that children in the sample have lower anthropometric measures compared to the reference population. On average, children in the sample are about two years old and approximately half of the children in the sample are female. In addition, over 80 percent of the children in the sample are alive during conflict.

Only 14 percent of children in the sample live in female-headed households. Further, household heads spend approximately 5 years receiving formal education. The average mother in the sample has relatively low educational attainment. About 75 percent of clusters in the sample are located in an urban area. On average, conflict-exposed clusters experienced about 7 conflict events and 12 conflict fatalities between August 2017 and their time of survey in 2018.

Overall, the unexposed clusters and conflict-exposed cluster samples seem to be balanced across dependent and independent variables except for children's WAZ and WHZ scores, household wealth index and mother's education level. On average, children living in conflict-exposed clusters have higher WAZ and WHZ scores compared to children in unexposed clusters, this difference is more pronounced in children's WHZ scores in both samples. In addition, households in conflict-exposed clusters have a higher wealth index, on average, compared to their counterparts in unexposed clusters. Further, the average mother education level in conflict-exposed clusters is slightly higher than that of unexposed clusters.

Table 1.1: Descriptive table for independent variables

Independent variables	Description	Expected signs
Conflict exposure	Dummy variable that takes the value of "1" if the household cluster is within 10km radius of at least one conflict event location between August 2017 and time of household survey in 2018 and takes the value of "0" if otherwise.	-
Farm household	Dummy variable that takes the value of "0" if neither the household head nor his or her spouse is engaged in agricultural occupation and takes the value of "1" if either the household head or his/her spouse is engaged in agricultural occupation	-
Alive during conflict	Dummy variable that takes the value of "0" if a child was born after conflict and "1" if the child was alive during conflict	+/-
Child's age	Age of the child in months	+/-
Female child	Dummy variable that takes the value of "0" if a child is male and "1" if the child is female	+/-
Household head age	The age of the household head in years	+
Female household head	Dummy variable that the value of "0" if a household head is male and "1" if the household head is female	-
Household size	The number of household members living in the household at the time of survey	+/-
Number of children	The number of children below 5 years living in the household at the time of survey	-
Household head years of education	The number of years household head spent in obtaining a formal education	+

Mother's education level	Is a categorical variable that takes the value of "1" for primary education, "2" for secondary education, and "3" for tertiary education.	+
Household wealth index	Composite wealth measure based on household assets (Television, refrigerator, motorcycle, car, and land) ownership adjusted for household region (rural/urban). The household wealth index is a continuous variable	+
Number of conflict incidences	The number of conflict incidences that occur within 10km radius of a cluster between August 2017 and 2018.	
Number of conflict fatalities	The number of conflict fatalities that occur within 10km radius of a cluster between August 2017 and 2018.	
Rural clusters	Is a dummy variable that takes the value of "1" if cluster are located in a rural area and "0" if they are located in an urban area.	

Table 1.2: Descriptive statistics

Variables	Total sample	Unexposed clusters	Conflict exposed clusters	Difference
Dependent variables				
MDDS	3.22	3.109	3.283	0.005
	(2.145)	(1.973)	(2.241)	(0.260)
WAZ	-0.71	-0.854	-0.625	0.342***
	(1.176)	(1.013)	(1.257)	(0.121)
WHZ	-0.19	-0.386	-0.071	0.365***
	(1.130)	(1.070)	(1.150)	(0.120)
HAZ	-0.99	-1.037	-0.964	0.183
	(1.297)	(1.318)	(1.287)	(0.138)
Independent variables				
Conflict exposure	0.63	0.000	1.000	1.000
	(0.484)	(0.000)	(0.000)	(0.000)
Alive during conflict	0.85	0.854	0.848	-0.012
	(0.357)	(0.354)	(0.360)	(0.041)
Child's age in months	23.29	22.570	23.707	1.094
	(17.52)	(17.381)	(17.614)	(2.096)
Child's gender	0.48	0.457	0.488	0.025
	(0.500)	(0.500)	(0.501)	(0.058)
Child’s birth order	2.96	3.020	2.926	-0.205
	(1.905)	(1.813)	(1.960)	(0.204)
Household head's age	39.95	41.000	39.328	-1.757
	(12.18)	(12.836)	(11.751)	(1.302)
Household head's gender	0.14	0.159	0.137	-0.026
	(0.352)	(0.367)	(0.344)	(0.037)
Number of children	2.12	2.079	2.141	-0.053

	(0.860)	(0.853)	(0.865)	(0.089)
Household head's years of education	4.70	4.709	4.688	0.119
	(1.599)	(1.565)	(1.622)	(0.072)
Mother's education level	1.94	1.881	1.971	0.084*
	(0.773)	(0.692)	(0.819)	(0.043)
Household wealth index	16811.04	11,623.298	19,870.992	17,755.664**
	(90851.5)	(85,782.797)	(93,742.625)	(6,931.543)
Rural clusters	0.25	0.338	0.195	0.000
	(0.434)	(0.475)	(0.397)	(0.000)
Conflict incidences (10km)	4.45	0.000	7.245	6.107***
	(4.424)	(0.000)	(3.403)	(0.174)
Conflict fatalities (10km)	7.26	0.000	11.805	8.580***
	(14.14)	(0.000)	(16.482)	(0.729)
Number of children	407	151	256	407

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS and ACLED.

1.4. Empirical strategy

To estimate the causal impact of Farmer-Herder conflict on children's WAZ, WHZ, and HAZ scores, the study exploits the spatial variation in the conflict events and variation in conflict exposure across birth cohorts. The study used a difference-in-difference approach, which relies on the assumption that, on the average, children's WAZ, WHZ, and HAZ scores would be similar across birth-cohorts in both conflict-exposed clusters and unexposed clusters in the absence of Farmer-Herder conflict events. Hence, the study's difference-in-difference model takes the following form:

$$\begin{aligned} y_{ihjcg} = \beta_o + \ & \beta_1 Alive\ during\ conflict_{ij} + \beta_2 Exposed\ cluster_c \\ & + \beta_3 Alive\ during\ conflict_{ij} * Exposed\ cluster_c + \beta_4 W'_{ihjcg} \\ & + \beta_5 X'_{hcg} + \beta_6 Z'_{cg} + \delta_c + \theta_j + \varphi_i + \gamma_i + \omega_i + \tau_g + e_{ihjcg} \end{aligned} \tag{1}$$

Where y_{ihjcg} is the WAZ, WHZ, or HAZ score of a child *i* living in household h in cohort j located in cluster c in cluster group g.

$Alive\ during\ conflict_{ij}$ is binary variable which takes the value of 1 if child *i* is alive during conflict.

$Exposed\ cluster_c$ is a binary variable which takes the value of 1 if cluster *c* is within 20km of conflict exposure radius.

W'_{ihjcg} is a vector of children's characteristics.

X'_{hcg} is a vector of household-level characteristics.

Z'_{cg} is a vector of cluster-level characteristics.

δ_c is the cluster exposure fixed effect.

θ_j is the birth cohort fixed effect.

φ_i is child's month of birth fixed effect.

γ_i is child's year of birth fixed effect.

ω_i is child's birth order fixed effect.

τ_g is the cluster group fixed effect.

e_{ihjcg} is the error term.

To analyze the differential impact of conflict on the nutritional and health outcomes of children living in farm households, we employed a triple difference model depicted by the empirical equation below:

$$\begin{aligned} y_{ihjcg} = \beta_o + \beta_1 Alive\ during\ conflict_{ij} + \beta_2 Exposed\ cluster_c \\ + \beta_3 Farm\ household_{ih} + \beta_4 Alive\ during\ conflict_{ij} \\ * Exposed\ cluster\ _c + \beta_5 Farm\ household_{ih} * Exposed\ cluster_c \\ + \beta_6 Farm\ household_{ih} * Alive\ during\ conflict_{ij} + \beta_7 Farm\ household_{ih} \\ * Exposed\ cluster_c * Alive\ during\ conflict_{ij} + \beta_8 W'_{ihjcg} + \beta_9 X'_{hcg} \\ + \beta_{10} Z'_{cg} + \delta_c + \theta_j + \tau_g + \varphi_i + \gamma_i + \omega_i + e_{ihjcg} \end{aligned} \tag{2}$$

Where $Farm\ household_{ih}$ is a binary variable that takes the value of 1 if child *i* lives in a farm household.

In equation 1, β_1 estimates how being alive during conflict affects a child's anthropometric scores while β_2 estimates the effects of living in a conflict-exposed cluster on a child's anthropometric scores. The coefficient of interest is β_3 , which estimates the interaction of $Post_{ij} * Exposed_c$. β_3 measures how the combined effect of being alive during the conflict and living in a cluster within 10km of a conflict location affect a child's anthropometric scores.

θ_j is the birth cohort fixed effect which controls for which helps to control for time invariant unobserved heterogeneity that pertains to being born at an earlier period compared to being born in a later period. δ_c is the cluster exposure fixed effect that accounts for time invariant unobserved characteristics that are specific to conflict-exposed clusters. Child's month of birth, year of birth and birth order fixed effects are included in the model to control for confounding factors related to a child's month of birth, year of birth, and birth order, respectively.

Specifically, a child's month of birth fixed effect controls for confounding factors related to child's month of birth such as seasonal variation in disease prevalence, food availability and household income. A child's birth order fixed effect could account for unobserved heterogeneity related to child's year of birth such as economic shocks, political instability, and weather-related shocks. Meanwhile child's birth order fixed effects controls for unobserved heterogeneity of being an earlier born versus later born, for instance, parents may allocate more resources to their earlier born children compared to their later born children.

As stated in the previous section, conflict events do not occur haphazardly; hence, conflict-exposed clusters might have certain characteristics that differentiate them from clusters that are not affected by Farmer-Herder conflict. If unobservable cluster characteristics (such as level of agricultural activity in the cluster, cluster's agroclimatic conditions, and education level of the cluster residents) which could self-select clusters into conflict are correlated with unobservable characteristics that affects children anthropometric measure it could result in selection bias.

To address this potential source of endogeneity, a caliper matching technique is employed to create comparable groups between conflict-exposed and unexposed clusters. The caliper matching is conducted on a set of predefined covariates: the average education level of household heads within the cluster, the cluster's average mother education level, the proportion of non-Fulani households, the share of households engaged in farming. Further, clusters are exactly matched based on cluster's rural-urban status, region, and state.

Each matched pair, termed a 'cluster group', consists of one conflict-exposed and one unexposed cluster that are similar across these covariates. The cluster group fixed effect, τ_g controls for all observable and unobservable characteristics that are constant within each pair of matched clusters. For the purpose of this study, we discussed the caliper matching scenario used in our analysis while the six other matching strategies attempted in this study are further discussed in Appendix B.

Caliper matching.

As discussed in the previous section, the caliper matching method was utilized on the sample obtained from the no matching scenario[6], which entails matching clusters within a predetermined caliper width based on specific matching variables. These variables included the average educational level of household heads, the average mother's education level, the proportion of non-Fulani households, and the proportion of households involved in farming within each cluster. Additionally, exact matching was implemented based on geographical factors such as the rural-urban status, region, and state of each cluster. Clusters were matched with no replacements.

By matching conflict-exposed clusters with unexposed clusters, we can define children's birth cohorts in unexposed clusters using the time of the last conflict event in the matched conflict-exposed cluster, since unexposed clusters by definition have not been exposed to conflict. A new cluster group variable is generated such that matching variables values are within the same +/- caliper width for all matched clusters in each group.

One potential drawback of the caliper matching method is that it employs a greedy match algorithm to match unexposed clusters to conflict-exposed clusters. This implies that the first group of conflict-exposed clusters would be matched to all possible unexposed clusters that fit the matching criteria, resulting in some conflict-exposed clusters not being matched to unexposed clusters despite the availability of potential unexposed clusters in the sample. To prevent this occurrence, the maximum number of unexposed clusters matched to each conflict-exposed cluster is restricted to one.

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[6] In the no matching scenario, conflict-exposed clusters are matched with unexposed clusters, provided they are located within the same state or region and share the same rural or urban status. If there isn't a suitable match for a conflict-exposed cluster or for an unexposed cluster, those clusters are excluded from the sample used in this scenario. .

Table 1.3 displays the difference in means between the matching variables in the conflict-exposed clusters and unexposed clusters before and after employing the caliper matching method. In the No matching scenario, there was a statistically significant difference in the proportion of Non-Fulani households between unexposed and conflict-exposed clusters. This difference, albeit small, could have significant implications given the potential for ethnic composition to influence both a cluster's likelihood of being drawn into conflict. As discussed in the background section, the Farmer-Herder conflict events have a distinct ethnic dimension. Predominantly, the herders engaged in these conflicts belong to the Fulani ethnic group, whereas the farmers involved are usually from various non-Fulani ethnic communities.

Table 1.3: Difference in Means of Household Characteristics Before and After Caliper Matching

Variable	(1) Unexposed cluster	(2) Conflict-exposed cluster	(3) Difference
Matching variables			
No matching			
Non-Fulani households	0.963	0.952	0.025*
	(0.189)	(0.214)	(0.014)
Farm households	0.444	0.230	-0.124***
	(0.497)	(0.422)	(0.032)
Mother’s education level	1.577	1.922	0.313***
	(0.897)	(0.832)	(0.061)
Household head years of education	5.046	5.077	0.004
	(1.442)	(1.574)	(0.125)
Rural households	0.404	0.252	0.000
	(0.491)	(0.435)	(0.000)
Number of children	*1020*	*394*	*1414*
Number of households	*782*	*230*	*1012*
Number of clusters	*326*	*76*	*402*
Caliper matching			
Non-Fulani households	1.000	1.000	0.000
	(0.000)	(0.000)	(0.000)
Farm households	0.264	0.222	-0.020
	(0.442)	(0.417)	(0.026)
Mother’s education level	1.829	1.819	-0.096

	(0.751)	(0.931)	(0.063)
Household head years of education	4.815	4.770	0.089
	(1.507)	(1.609)	(0.092)
Rural households	0.333	0.240	-0.000
	(0.473)	(0.428)	(0.000)
Number of children	*169*	*298*	*467*
Number of households	*129*	*171*	*300*
Number of clusters	*54*	*54*	*108*

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS(2018) and ACLED.

There is a significant difference in the proportion of farm households between conflict-exposed and unexposed clusters. This finding is especially pertinent in the context of Farmer-Herder conflicts. Regions with intensive agricultural activities may inadvertently attract herders seeking grazing grounds for their cattle.

Moreover, these agricultural activities, which are vital for both the sustenance and economic stability of farming communities, are frequently and severely disrupted in areas affected by Farmer-Herder conflicts. Such disruptions not only jeopardize household's food security, in general, but it also affects the income of farm households. This, in turn, may have a direct and adverse effect on the nutritional status of children in conflict-exposed households.

Additionally, there was a notable difference in the mother's education level between conflict-exposed and unexposed clusters. Given the established correlation between maternal education and child health outcomes – encompassing aspects such as healthcare choices, nutrition, and hygiene practices – this difference is particularly salient. In conflict scenarios, higher levels of maternal education in the cluster may be a signal for the wealth of the cluster residents which may affect cluster's exposure to conflict. Further, households with high maternal education may have better ability to mitigate the effects of conflict, potentially influencing both their exposure to conflict and their capacity to protect their children's health.

After employing the caliper matching method, results in Table 1.3 reveal that the matching variables are balanced across conflict-exposed and unexposed clusters. The difference in the proportion of non-Fulani households across both conflict-exposed and unexposed clusters was completely eliminated, achieving an exact match. Similarly, the discrepancy in the proportion of farm households and average maternal education level was significantly reduced.

Although employing the caliper matching method helps to achieve balance across conflict-exposed cluster and unexposed clusters in the sample, it also resulted in a substantial decrease in sample size. The number of children in the study reduced by 24.4% and 83.4% post-matching in conflict-exposed and unexposed clusters, respectively. Consequently, the number of households and clusters in the sample also saw substantial reductions.

While a decrease in sample size post matching is necessary for achieving balance, it raises concerns about the representativeness of the matched sample. Furthermore, the reduced sample size could impact the statistical power of our analysis, potentially limiting our ability to detect smaller, yet meaningful, effects of conflict on children's health outcomes. While caliper matching helps to control for selection bias, the implications of data reduction on representativeness and statistical power remain important considerations in interpreting the study's findings.

As discussed in the previous section of this chapter, the study focused on conflict events occurring after the passing of anti-open grazing laws in 2017, specifically from August 2017 to the time of survey in 2018. The oldest child in the study was born in September 2013. By limiting the analysis to conflicts after the passing of anti-open grazing laws, the study may underestimate the impact conflicts from 2017 if earlier conflicts (from September 2013 to July 2017) significantly impacted child anthropometric measures. This limitation arises because some clusters exposed to conflicts during this earlier period are categorized as unexposed in the current analysis framework.

Furthermore, Table A.5 shows that after caliper matching, about 44% of conflict-exposed clusters from the extended period (September 2013 to survey time in 2018) are excluded in the analysis for the post-2017 conflict period.[7] To address this potential underestimation and provide a more accurate assessment of the impact of conflict on children's anthropometric measures, the study conducted a robustness check. This check involved restricting the children's age in the study sample to those born during the specific conflict period used in the analysis, i.e., between August 2017 and December 2018.

Parallel trends

Our identification strategy relies on the parallel trend assumption, which implies that the difference in outcomes between children in the exposed and unexposed clusters would not change in the absence of conflict. Conventionally, justification is provided for the parallel trend assumption by testing whether the pre-treatment outcomes between the treated and control group are trending in the same way. However, we are using cross-sectional data and a difference-in-difference method which exploits the variation in conflict exposure based on birth timing. Hence, our pre-treatment group is the "born after conflict" cohort because it is the birth cohort which is unexposed to conflict.

To provide empirical support for the potential plausibility of the parallel trend assumption, we regressed the outcome variables on the interaction term of conflict exposure and children's age in months for children in the born after conflict cohort. Table 1.4 below shows that there is no statistically significant difference in children's outcomes between children living in conflict-exposed clusters and those living in unexposed clusters across age categories in the "born after conflict"

[7] August 2017 to time of survey in 2018

cohort. However, given the small number of observations, this is a low-power test and offers only suggestive evidence.

Table 1.4: Regression for parallel trend assumption

	WAZ	WAZ	WHZ	WHZ	HAZ	HAZ
Exposed cluster (10km)	0.617^{**}	-1.179	-0.042	1.641	1.004	-3.707
	(0.242)	(1.552)	(0.662)	(3.153)	(0.681)	(3.423)
Child's age (base = below 3 months)						
3 - 4 months old		-1.210		2.689		-5.625
		(3.130)		(5.349)		(4.717)
Over 5 months old		-1.349		2.303		-5.863
		(4.932)		(7.174)		(5.944)
3 - 4 months old * Exposed cluster		0.976		-2.819		4.474
		(1.971)		(3.898)		(4.170)
Over 5 months old * Exposed cluster		2.242		-1.293		4.793
		(2.959)		(4.606)		(5.338)
Constant	-4.935^{***}	-6.228	0.031	0.440	-6.791	-8.333
	(1.403)	(3.865)	(3.296)	(7.878)	(4.734)	(6.369)
R-squared	0.661	0.814	0.310	0.642	0.315	0.618
Number of children	39	39	39	39	39	39

Robust standard errors clustered at the household cluster level are reported in parenthesis. The dependent variable in column (1) and column (2) is *Weight-for-Age Z score*, in column (3) and (4), it is *Weight-for-height Z scores*, and in column (5) and (6), it is *Height-for-Age Z score*. Independent variables include *Conflict Exposure* which takes the value of "1" if cluster is located within 10km radius of a conflict event and "0" if otherwise; *Child's age* is a categorical variable that measures the age of child in months. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS and ACLED.

1.5. Results

Table 1.5 presents the results on the impact of conflict on children's WAZ scores. The difference-in-difference estimates are reported in the second and third columns of the table, while the last five columns present the coefficient estimates from the triple difference analysis. Findings reveal that conflict has no statistically significant impact on children's WAZ. In addition, household wealth has a positive impact on children's WAZ scores, but the magnitude is infinitesimally small.

The fourth column of Table 1.5 shows that conflict has no impact on children in farm households. However, with the inclusion of control variables in the fiftth column, the effect of conflict on children in farm households is negative and statistically significant. Since the average child's WAZ score in the sample is lower than the reference population mean, exposure to conflict would cause underweight in an average child living in a farm household.

The impact of conflict on children living in farm households is consistent when children's month of birth fixed effect is controlled for, as shown in the sixth column of Table 1.5. However, the magnitude slightly decreases, suggesting a downward bias in the result presented in the fifth column. Since the children's month of birth fixed effect controls for time-invariant unobserved heterogeneity such as seasonality of food prices or infectious diseases, it is plausible that the reason for the downward bias in the result presented in the third column could be that other unobserved factors, such as seasonality of food prices and infectious disease may be partly responsible for lower WAZ scores in children living in farm households.

The result presented in the seventh column of Table 1.5 isolates the impact of conflict on children living in farm households from unobserved factors related to the child's year of birth, such as drought, famine, and inflation, which affect children's WAZ scores. Similar to the findings reported in the sixth column of the table, the result remains the same, but the magnitude decreased slightly.

This finding implies that the result in the fifth column is biased downward, and some of the negative impact of conflict on the WAZ score that was observed in the fifth column is not entirely due to the Farmer-Herder conflict event but due to unobserved heterogeneity pertaining to children's year of birth.

The result presented in the last column suggests that conflict impact on WAZ score becomes more detrimental when birth order is controlled for. This implies that the result in fifth column is confounded by factors relating to a child's birth order. This could be due to various reasons, like resource allocation within families, where earlier-born children might receive more resources than their younger siblings.

Interestingly, children who live in farm households located in areas affected by conflict tend to have higher weight-for-age z-scores (WAZ) compared to other children in the same region. This finding is unexpected, as the assumption would be that children living in farm households in conflict-exposed clusters would have lower WAZ scores than their peers or that their WAZ scores would not differ significantly from those of other children. A plausible explanation for this result is that farm households are more self-sufficient than other households in conflict-exposed areas. In the event of market disruption and high food prices due to conflict, farm households may have better food self-sufficiency by consuming their crops.

Table 1.5: Effects of conflict on child Weight-for-Age Z-score

	WAZ	WAZ	WAZ	WAZ	WAZ	WAZ	WAZ
Alive during conflict	-0.186	-0.354	-0.359	-0.481	-0.462	-0.418	-0.358
	(0.276)	(0.301)	(0.283)	(0.298)	(0.320)	(0.373)	(0.306)
Exposed cluster	0.344	0.228	0.113	-0.010	-0.010	-0.018	0.105
	(0.284)	(0.281)	(0.266)	(0.278)	(0.278)	(0.265)	(0.305)
Alive during conflict * Exposed cluster	-0.168	0.081	0.188	0.339	0.319	0.338	0.209
	(0.314)	(0.307)	(0.318)	(0.318)	(0.324)	(0.311)	(0.338)
Farm household			-0.292	-1.338	-1.225	-1.249	-1.319
			(1.013)	(1.100)	(1.033)	(1.080)	(1.008)
Alive during conflict * Farm household			0.708	1.268	1.181	1.173	1.252
			(0.886)	(0.947)	(0.878)	(0.936)	(0.821)
Exposed cluster * Farm household			1.095	**2.042***	**1.800***	**1.984***	**2.193****
			(1.065)	**(1.079)**	**(1.004)**	**(1.061)**	**(1.014)**
Alive during conflict * Exposed cluster * Farm household			-1.493	**-2.137****	**-1.921***	**-2.035***	**-2.295****
			(1.060)	**(1.070)**	**(0.993)**	**(1.059)**	**(1.033)**
Child's age		0.001		0.002	0.001	-0.028*	-0.001
		(0.004)		(0.004)	(0.004)	(0.016)	(0.004)
Female child		-0.091		-0.066	-0.071	-0.077	-0.052
		(0.118)		(0.116)	(0.111)	(0.118)	(0.122)
Household head age		0.015		0.012	0.015	0.013	0.012
		(0.026)		(0.026)	(0.028)	(0.026)	(0.030)
Household head age^2		-0.000		-0.000	-0.000	-0.000	-0.000
		(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Female household head		-0.118		-0.116	-0.141	-0.138	-0.130
		(0.204)		(0.207)	(0.210)	(0.207)	(0.191)
Number of children		0.050		0.043	0.039	0.040	0.075
		(0.086)		(0.087)	(0.088)	(0.089)	(0.099)
Household head years of education		0.037		0.007	0.031	0.006	-0.004
		(0.085)		(0.083)	(0.093)	(0.085)	(0.079)
Household wealth index		**0.000****		**0.000****	**0.000****	**0.000****	**0.000****
		(0.000)		**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Constant	-0.734***	-1.168*	-0.694***	-0.824	-0.972	-0.192	-0.901
	(0.253)	(0.684)	(0.241)	(0.733)	(0.750)	(0.816)	(0.819)
Month of birth fixed effect	*No*	*No*	*No*	*No*	*Yes*	*No*	*No*
Year of birth fixed effect	*No*	*No*	*No*	*No*	*No*	*Yes*	*No*
Birth order fixed effect	*No*	*No*	*No*	*No*	*No*	*No*	*Yes*
R-squared	0.020	0.057	0.036	0.075	0.070	0.078	0.080
Number of children	459	408	459	408	408	408	407

Robust standard errors clustered at the cluster level are reported in parenthesis. The dependent variable is Weight-for-Age Z score. The variables of interest are C*onflict exposure*, *Alive during conflict,* and *Farm household. Conflict exposure* is the *Treatment* variable that takes the value of "1" if cluster is within 10km radius of at least one conflict event between August 2017 and time of household survey (Nigeria DHS 2018 survey was conducted from August 2018 to December 2018) and "0" if otherwise. *Alive during conflict* is the *Post* variable that takes the value of "1" if a child was alive during conflict and "0" if the child was born after conflict ended in their cluster. Farm household takes the value of 1 if household head or their spouse are engaged in agriculture occupation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS an

Table 1.6: Effects of conflict on child Weight-for-Height Z-score

	WHZ	WHZ	WHZ	WHZ	WHZ	WHZ	WHZ
Alive during conflict	-0.188	-0.454	-0.266	-0.445	-0.374	-0.512	-0.385
	(0.317)	(0.343)	(0.372)	(0.397)	(0.418)	(0.431)	(0.386)
Exposed cluster	0.256	0.183	0.220	0.140	0.182	0.129	0.183
	(0.261)	(0.296)	(0.293)	(0.315)	(0.330)	(0.313)	(0.316)
Alive during conflict * Exposed cluster	-0.001	0.203	0.257	0.318	0.248	0.319	0.267
	(0.301)	(0.326)	(0.352)	(0.362)	(0.384)	(0.363)	(0.362)
Farm household			**1.074****	0.608	0.786	0.666	0.605
			(0.533)	(0.652)	(0.600)	(0.635)	(0.635)
Alive during conflict * Farm household			-0.309	-0.064	-0.177	-0.124	-0.047
			(0.507)	(0.562)	(0.516)	(0.548)	(0.534)
Exposed cluster * Farm household			-0.462	0.325	0.062	0.294	0.396
			(0.627)	(0.686)	(0.648)	(0.678)	(0.680)
Alive during conflict * Exposed cluster * Farm household			-0.254	-0.599	-0.412	-0.545	-0.654
			(0.669)	(0.704)	(0.656)	(0.693)	(0.701)
Child's age		**0.007***		**0.007***	**0.007***	-0.011	0.005
		(0.004)		**(0.004)**	**(0.004)**	(0.015)	(0.004)
Female child		-0.166		-0.162	-0.156	-0.163	-0.155
		(0.116)		(0.116)	(0.111)	(0.117)	(0.121)
Household head age		-0.012		-0.012	-0.005	-0.015	-0.007
		(0.027)		(0.027)	(0.029)	(0.027)	(0.029)
Household head age^2		0.000		0.000	0.000	0.000	0.000
		(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Female household head		-0.206		-0.224	-0.232	-0.239	-0.220
		(0.222)		(0.221)	(0.229)	(0.225)	(0.219)
Number of children		0.082		0.084	0.062	0.085	0.119
		(0.077)		(0.077)	(0.078)	(0.078)	(0.089)
Household head years of education		-0.062		-0.056	-0.043	-0.055	-0.070
		(0.086)		(0.093)	(0.101)	(0.099)	(0.092)
Household wealth index		0.000		0.000	0.000	0.000	0.000
		(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.229	0.404	-0.380	0.184	-0.028	0.715	0.044
	(0.277)	(0.725)	(0.298)	(0.772)	(0.801)	(0.813)	(0.856)
Month of birth fixed effect	*No*	*No*	*No*	*No*	*Yes*	*No*	*No*
Year of birth fixed effect	*No*	*No*	*No*	*No*	*No*	*Yes*	*No*
Birth order fixed effect	*No*	*No*	*No*	*No*	*No*	*No*	*Yes*
R-squared	0.017	0.071	0.044	0.082	0.073	0.076	0.081
Number of children	458	407	458	407	407	407	406

Robust standard errors clustered at the household cluster level are reported in parenthesis. The dependent variable is Weight-for-Height Z score. The variables of interest are C*onflict exposure*, *Alive during conflict,* and *Farm household. Conflict exposure* is the *Treatment* variable that takes the value of "1" if cluster is within 10km radius of at least one conflict event between August 2017 and time of household survey (Nigeria DHS 2018 survey was conducted from August 2018 to December 2018) and "0" if otherwise. *Alive during conflict* is the *Post* variable that takes the value of "1" if a child was alive during conflict and "0" if the child was born after conflict ended in their cluster. Farm household takes the value of 1 if household head or their spouse are engaged in agriculture occupation. * p < 0.10, ** p < 0.05, *** p < 0.01. Source: Nigeria DHS and ACLED.

Table 1.6 presents analysis estimates of the impact of conflict on children's Weight-for-Height Z-scores (WHZ). Findings show that conflict has a negative but statistically insignificant impact on children's WHZ scores, including those in farm households. In addition, results show that older children tend to have higher WHZ scores.

Table 1.7 presents the impact of conflict on children's HAZ scores. Similar to the findings in Table 1.5, conflict has no statistically significant impact on children's HAZ scores in general. However, the fifth column in the table reports that children living in farm households have lower HAZ scores than their counterparts. Interestingly, children who are alive during conflict living in farm households have higher HAZ scores compared to their counterparts.

This finding may suggest that children who are alive during conflict living in farm households, irrespective of whether their households are located in conflict-exposed clusters, have better HAZ scores. However, this impact is not statistically significant when the child's month of birth and year of birth fixed effect are included in the sixth column. This implies that the HAZ scores of children who are alive during conflict living in farm households are better off than those of their counterparts due to favorable factors relating to the timing of their birth.

Moreover, children living in farm households located in exposed clusters have higher WAZ scores; this finding is similar to the results in Table 1.5 on how living in conflict-exposed clusters affects farm households' children's WAZ scores. In addition, the magnitude of the impact decreases with the inclusion of children's month of birth and year of birth fixed effects, while the magnitude increases with the inclusion of the child's birth order fixed effects. This result pattern is similar to that observed in Table 1.5 on how living in conflict-exposed clusters affects farm households' children's WAZ.

While conflict has no statistically significant impact on children's HAZ scores, in general, it has a statistically significant impact on HAZ scores of children living in farm households. This magnitude of the impact is slightly higher than that observed for WAZ scores in Table 1.5. However, the pattern of the results remains the same. Similar to WAZ scores, the magnitude of the impact slightly reduces with the inclusion of children's month-of-birth fixed effects and year-of-birth fixed effects in the model. However, the estimated magnitude increases when children's birth order fixed effect is included in the last column.

Table 1.7: Effects of conflict on child Height-for-Age Z-score

	HAZ	HAZ	HAZ	HAZ	HAZ	HAZ	HAZ
Alive during conflict	-0.392	-0.387	-0.559*	-0.559	-0.528	-0.139	-0.439
	(0.303)	(0.361)	(0.306)	(0.346)	(0.360)	(0.426)	(0.363)
Exposed cluster	0.249	0.151	-0.028	-0.148	-0.169	-0.143	-0.032
	(0.323)	(0.353)	(0.323)	(0.349)	(0.332)	(0.341)	(0.374)
Alive during conflict * Exposed cluster	-0.202	-0.021	0.026	0.224	0.241	0.188	0.097
	(0.358)	(0.388)	(0.378)	(0.398)	(0.383)	(0.396)	(0.416)
Farm household			-1.514	**-2.633****	**-2.544****	**-2.527****	**-2.629****
			(1.044)	**(1.138)**	**(1.148)**	**(1.111)**	**(1.080)**
Alive during conflict * Farm household			1.334	**1.792***	1.698	1.635	**1.792***
			(0.943)	**(1.013)**	(1.040)	(1.002)	**(0.923)**
Exposed cluster * Farm household			**1.967***	**2.571****	**2.402****	**2.483****	**2.727****
			(1.097)	**(1.136)**	**(1.171)**	**(1.112)**	**(1.077)**
Alive during conflict * Exposed cluster * Farm household			-1.802	**-2.426****	**-2.238***	**-2.250***	**-2.632****
			(1.143)	**(1.151)**	**(1.193)**	**(1.138)**	**(1.104)**
Child's age		-0.005		-0.005	-0.006	**-0.044****	-0.007
		(0.004)		(0.004)	(0.004)	**(0.021)**	(0.004)
Female child		0.079		0.113	0.087	0.077	0.126
		(0.133)		(0.130)	(0.134)	(0.136)	(0.134)
Household head age		0.028		0.024	0.022	0.032	0.023
		(0.032)		(0.032)	(0.033)	(0.031)	(0.035)
Household head age^2		-0.000		-0.000	-0.000	-0.000	-0.000
		(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Female household head		0.031		0.053	-0.010	0.032	0.028
		(0.217)		(0.227)	(0.216)	(0.223)	(0.210)
Number of children		0.018		0.008	0.032	-0.003	0.023
		(0.086)		(0.085)	(0.087)	(0.087)	(0.097)
Household head years of education		0.089		0.039	0.055	0.031	0.041
		(0.078)		(0.079)	(0.087)	(0.068)	(0.075)
Household wealth index		**0.000*****		**0.000****	**0.000****	**0.000****	**0.000****
		(0.000)		**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Constant	-0.773***	-1.882**	-0.564**	-1.143	-1.171	-0.669	-1.242
	(0.270)	(0.759)	(0.263)	(0.781)	(0.774)	(0.886)	(0.828)
Month of birth fixed effect	*No*	*No*	*No*	*No*	*Yes*	*No*	*No*
Year of birth fixed effect	*No*	*No*	*No*	*No*	*No*	*Yes*	*No*
Birth order fixed effect	*No*	*No*	*No*	*No*	*No*	*No*	*Yes*
R-squared	0.025	0.055	0.039	0.087	0.081	0.076	0.094
Number of children	459	408	459	408	408	408	407

Robust standard errors clustered at the household cluster level are reported in parenthesis. The dependent variable is Height-for-Age Z score. The variables of interest are C*onflict exposure*, *Alive during conflict,* and *Farm household. Conflict exposure* is the *Treatment* variable that takes the value of "1" if cluster is within 10km radius of at least one conflict event between August 2017 and time of household survey (Nigeria DHS 2018 survey was conducted from August 2018 to December 2018) and "0" if otherwise. *Alive during conflict* is the *Post* variable that takes the value of "1" if a child was alive during conflict and "0" if the child was born after conflict ended in their cluster. Farm household takes the value of 1 if household head or their spouse are engaged in agriculture occupation. * p < 0.10, ** p < 0.05, *** p < 0.01. Source: Nigeria DHS and ACLED.

Heterogeneity in the impact of conflict

Studies (Bruck et al., 2016; Mercier et al., 2016; Baliki et al., 2017) have shown that conflict has a differential impact among subpopulations based on individual demographics and household socioeconomic factors. Table 1.8 presents the regression results on the differential impact of fatal conflict on children based on their gender. The results indicate no statistically significant difference in the impact of conflict exposure on children's WAZ scores based on gender.

Similarly, findings show that conflict exposure has no differential impact on children's HAZ scores based on gender. Although results in the third column of Table 1.8 suggest that children who are alive during conflict have lower HAZ scores; this finding is not robust to the inclusion of control variables. Results in Table 1.9 also reveal that conflict has no differential impact on a child's WAZ and HAZ score based on household wealth.

Table 1.8: Heterogeneity in the impact of conflict by child's gender

	WAZ	WAZ	HAZ	HAZ
Alive during conflict	-0.463	-0.463	-0.642*	-0.412
	(0.377)	(0.449)	(0.348)	(0.434)
Exposed cluster (10km)	0.260	0.596	0.228	0.602
	(0.383)	(0.493)	(0.374)	(0.518)
Alive during conflict * Exposed cluster	0.013	0.018	-0.383	-0.297
	(0.420)	(0.481)	(0.451)	(0.522)
Female child	-0.519	-0.313	-0.680	-0.429
	(0.693)	(0.700)	(0.846)	(0.845)
Alive during conflict * Female child	0.683	0.386	0.715	0.419
	(0.703)	(0.742)	(0.886)	(0.915)
Exposed cluster * Female child	0.193	0.036	0.116	0.130
	(0.755)	(0.807)	(0.964)	(1.007)
Alive during conflict * Exposed cluster * Female child	-0.431	-0.217	0.253	0.154
	(0.765)	(0.845)	(1.022)	(1.079)
Constant	-0.516	-1.126	-0.504*	-2.524***
	(0.356)	(0.884)	(0.293)	(0.898)
Control	*No*	*Yes*	*No*	*Yes*
Month of birth fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
R-squared	0.023	0.054	0.045	0.072
Number of children	444	393	444	393

Robust standard errors clustered at the household cluster level are reported in parenthesis. The dependent variables are Weight-for-Age Z score and Height-for-Age Z score. The variables of interest are *Exposed cluster, Alive during conflict*, and *Female child*. *Exposed cluster* is the *Treatment* variable that takes the value of "1" if cluster is within 10km radius of at least one conflict event from August 2017 to the time of household survey (Nigeria DHS 2018 survey was conducted from August 2018 to December 2018) and "0" if otherwise. *Alive during conflict* is the *Post* variable that takes the value of "1" if a child was alive during conflict and "0" if the child was born after conflict ended in their cluster. *Female child* is a dummy variable takes the value of 1 if a child is female and takes the value of "0" if the child is male. Other independent variables used include *child's age in months, child's gender, household head age, household head gender, household head years of education, household size, number of children in the household, and household's wealth index*. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS and ACLED

Table 1.9: Heterogeneity in the impact of conflict by household wealth index

	WAZ	WAZ	HAZ	HAZ
Alive during conflict	-0.200	-0.357	-0.306	-0.079
	(0.345)	(0.437)	(0.393)	(0.544)
Exposed cluster (10km)	0.209	0.402	0.204	0.910
	(0.357)	(0.526)	(0.415)	(0.619)
Alive during conflict * Exposed cluster	-0.088	0.023	-0.220	-0.365
	(0.394)	(0.466)	(0.451)	(0.574)
Household wealth index	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Alive during conflict * Household wealth index	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Exposed cluster * Household wealth index	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Alive during conflict * Exposed cluster * Household wealth index	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.698**	-1.130	-0.811**	-2.309***
	(0.325)	(0.892)	(0.368)	(0.875)
Controls	No	Yes	No	Yes
Child month of birth fixed effect	Yes	Yes	Yes	Yes
R-squared	0.068	0.080	0.050	0.073
Number of children	444	393	444	393

Robust standard errors clustered at the household cluster level are reported in parenthesis. The dependent variables are Weight-for-Age Z score and Weight-for-Height Z score. The variables of interest are *Exposed cluster, Alive during conflict*, and *Household wealth index*. Exposed cluster is the Treatment variable that takes the value of "1" if cluster is within 10km radius of at least one conflict event from August 2017 to the time of household survey (Nigeria DHS 2018 survey was conducted from August 2018 to December 2018) and "0" if otherwise. Alive during conflict is the Post variable that takes the value of "1" if a child was alive during conflict and "0" if the child was born after conflict ended in their cluster. The household wealth index variable is a continuous variable. Other independent variables used includes child's age in months, child's gender, child's birth order, household head age, household head gender, household head years of education, household size, number of children in the household, mother's education level, and number of conflict events in the cluster from August 2017 to the time of household survey. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS and ACLED

Robustness check

Alternative Matching Variables and Measures for Conflict Exposure

Figures A.1 and A.2 report the baseline estimates for conflict impact on children's WAZ and HAZ scores and the corresponding estimates obtained from altering the triple difference model and the caliper matching variables. We introduced a potential matching variable into our study's original matching variables used for caliper matching. Furthermore, we substituted the conflict exposure at a 10km radius in the triple difference model for conflict exposure at a 20km radius.

We also substituted conflict exposure at a 10km radius for fatal conflict exposure at a 10km radius. The fatal conflict exposure variable is a dummy variable that takes the value of 1 if the household is exposed to at least one fatal conflict event between August 2017 and December 2018. Further, we removed the 15 days buffer that accounts for conflict lingering impact in our analysis and redefine birth cohort based on the last conflict event in the cluster.

Figure A.1 shows that the regression estimates on the impact of conflict on the WAZ score of a child living in a farm household is robust to the inclusion of a matching variable, which represents the average household land ownership in the cluster. In addition, results were robust with the removal of the 15 days buffer that accounts for conflict lingering impact across birth cohorts.

Similarly, Figure A.2 reveals that our analysis of the impact of conflict on farm households' children's HAZ scores is robust to including the average household land ownership in the cluster as a matching variable. Further, the analysis estimate on the impact of conflict on the HAZ scores of children in farm households is robust to the substitution of conflict exposure at a 10km radius for conflict exposure at a 20km radius and fatal conflict exposure at a 10km exposure radius. Moreover, results were robust with the removal of 15 days lingering impact used in the original analysis.

The impact of conflict on children born between August 2017 and 2018

The result in Table A.1 presents the estimates of the impact of conflict on children born between August 2017 and 2018 in farm households. Findings show that children in farm households have lower HAZ scores than their peers. The disparity in HAZ scores is more profound when children in farm households are exposed to conflict. Similarly, the conflict has a negative impact on farm households' children's WAZ scores.

These findings align with the results presented in Tables 1.5 and 1.7; however, the magnitude of the estimates is notably larger. This suggest that by limiting our sample to children born between August 2017 and 2018 - a period when the farmer-herder conflict events and fatalities escalated - we are more accurately capturing the impact of the conflict events during the period.

Mechanism of impact

One of the pathways through which conflict may affect children's nutrition is explored in Table A.2, which reports the estimates of the impact of conflict exposure on children's dietary diversity scores. We found that children in farm households have higher dietary diversity than their counterparts. Similarly, children in farm households exposed to conflict have higher dietary diversity, although the magnitude is slightly smaller. The results in Table A.2 are robust to the addition of children's birth order fixed effect and household month of survey fixed effect.

Further, the finding supports the assumption that farm households in conflict-exposed clusters are more food self-sufficient than their peers.

Another potential pathway through which conflict may affect children's WAZ and HAZ scores is through health factors such as access to healthcare. Table A.3 presents results on the impact of conflict on children's intake of essential medications, while Table A.4 displays estimates on the impact of conflict on mother's healthcare during pregnancy.

Findings show that children in farm households are less likely to receive iron pills. However, there is no differential impact of conflict between children who are alive during conflict and those born after conflict in terms of essential medication intake. Table A.4 reports the impact of conflict on mothers' antenatal care. Results show that mothers living in farm households are less likely to receive antenatal care from healthcare facilities[8] compared to those living in non-farm households. Further, mothers living in farm households are less likely to receive antenatal care from healthcare facilities for children that are alive during conflict compared to children that are born after conflict. While results show that conflict has no impact on the frequency of antenatal visits or whether a mother received antenatal care from a formally trained healthcare provider, it has a statistically significant impact on whether a mother received antenatal care from a healthcare facility. The findings in Table A.2 to A.4 suggest that conflict could affect the anthropometric measures of children in farm households through access to maternal healthcare facilities, or that conflict simultaneously decreases child health and reduces access to antenatal care.

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[8] The healthcare facilities are government hospitals, health posts, private hospitals, and government health centers

Conclusion

This paper analyzes the impact of Farmer-Herder conflict on children's nutritional and health outcomes using a difference-in-difference analysis. Our findings show that conflict has a negative impact on children's WAZ and HAZ scores within a 10km radius of the conflict location. Our results are robust to the inclusion of alternative matching variables and conflict measures. However, the impact on WHZ scores was not statistically significant. Additionally, we discovered no differential impact in conflict exposure based on children's WAZ and HAZ scores based on household wealth and children's gender.

Our exploration into potential mechanisms suggests that conflict affects child anthropometric measures through channels other than food security. Hence, policymakers may focus on channels such as access to healthcare facilities to mitigate the impact of conflict on children's anthropometric scores. Future studies in this field should analyze other mechanisms through which conflict affects children's nutritional and health outcomes by exploring food security outcomes other than dietary diversity. In addition, investigating other non-food pathways through which conflict may influence children's anthropometric measures could offer a more comprehensive understanding of the multifaceted impact of conflict on child well-being.

This study has a couple of limitations worth noting. First, if conflict affects children in utero, we may be underestimating the true causal impact of conflict. However, due to data constraints, we cannot verify whether conflict does affect the children in utero within our study. Additionally, using cross-sectional data means our findings are specific to the impact of the farmer-herder conflict on nutritional and health outcomes in 2018. Generalizing these findings to other periods should be done cautiously.

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Chapter 2 - The impact of conflict on crop income in Nigeria.

2.1. Introduction

Farm households in Fragile and Conflict-Affected Situations (FCS) face multiple challenges in pursuing their source of livelihood. FCS often occur in developing countries (World Bank, 2023), where a substantial proportion of households are employed in the agricultural sector (Davis et al., 2017). Farm households in FCS experience low agricultural productivity due to conflict activities (Arias et al., 2019), and destruction of farm produce. Weak institutions further compound the challenges faced by farm households in FCS (Ragasa and Golan, 2014), thus amplifying the negative impacts of conflict on agricultural productivity.

Within FCS, the accessibility of markets emerges as a prominent concern, given that market areas often become arenas for conflict events (Pape et al., 2017). Farmers in FCS may grapple with unavailability of farm inputs and constrained accessibility to vital input markets (El Dahan and Darrington, 2016). Additionally, security concerns can impede middlemen's access to farmers' markets to procure produce (ICG, 2017), potentially leading to the spoilage of farm produce or high transaction costs. In the absence of middlemen, farmers may find themselves compelled to sell their produce at a reduced price as a result of excess supply and the constraint of primarily selling within their proximity. Understanding the effects of conflict on farm income and identifying the pathways through which conflict affects crop income is important in developing efficient policies to mitigate adverse impact on farm household welfare.

A majority of farm households in Sub-Saharan African countries depend on rain-fed agriculture (Rapsomanikis, 2015), utilizing relatively low fertilizer, pesticide, and mechanized farming practices (Christiaensen and Demeris 2018). These, coupled with extreme weather events, often predispose farm households to low and volatile yields (Garcia-Verdu et al., 2022; Lobell et al.,2011). Over the past few decades, increasingly frequent and escalating conflict events spanning across sub-Saharan Africa (Fang et al., 2020) pose an additional threat to farm households' livelihood. In this chapter, we analyze the impact of conflict on crop income and the mechanisms through which conflict affects crop income.

The Farmer-Herder conflict is one of the major conflict events which has grown prominent in recent years in Sub-Saharan Africa (Brottem, 2021). The conflict is primarily driven by competition over land and water resources between sedentary farmers and nomadic herders (Kratli and Toulmin, 2020; Turner, 2004). The conflict occurs annually, it typically peaks in January (ACLED, 2023). However, the interplay between the seasonal occurrence of Farmer-Herder conflict events and the seasonal nature of rainfed agriculture is poorly understood. Understanding the severity of conflict impact across various phases of the agricultural cycle is crucial in determining the optimal timing of policy implementation.

Several studies have been conducted on the impact of conflict on agricultural productivity and production decisions. In terms of farm output, studies have shown that conflict has a negative impact on total agricultural output, area of land harvested, and output of some specific crops and cattle holdings. In terms of farm input, Nnaji et al (2023) found that higher risk perception significantly reduced farm households fertilizer uses and investment.

Studies on the impact of farmer-herder conflict on farm labor supply have produced mixed results. Odozi and Oyelere (2021) found that, overall, conflict negatively affects farm household labor supply. However, George et al. (2021) found that while conflict reduced household labor hours, it did not significantly impact hired labor days. Adelaja and George (2019) revealed that the Boko-Haram conflict negatively impacted hired farm labor and wages but did not affect household labor supply. Yet, Nnaji et al. (2023) showed that higher risk perception of Farmer-Herder conflict significantly increased household labor supply on farms.

This study makes three key contributions to existing literature. Firstly, this study evaluates the causal impact of conflict on crop income in Nigeria. We analyzed the impact of conflict on crop income using Armed Conflict Location and Event Dataset (ACLED) and panel dataset obtained from the Nigeria General Household Survey Panel (GHSP) conducted in year 2010/11, 2012/13, and 2015/16. Understanding the interplay between conflict cycle and the agricultural cycle is important in identifying the critical period when farm households are most vulnerable. Hence, the second main contribution of our study is that we evaluate the heterogeneity in the impact of conflict across each phase of the agricultural cycle.

The third main contribution of our study is that we analyzed the pathway through which conflict affects crop income by evaluating the impact of conflict on the value of crop production and input costs. While studies have assessed the impact of conflict on agricultural output and input, there is a need to quantify the impact in monetary value. By evaluating how conflict influences both the value of crop production and costs of essential inputs, we quantify in monetary terms the overall economic losses suffered by farmers due to conflict. This nuanced approach enables an understanding of the true economic toll, encompassing direct production losses and indirect costs related to increased input usage. Moreover, assessing the impact in monetary terms is crucial for informing policy decisions, prioritizing interventions, and promoting sustainable agricultural development in conflict-affected regions.

2.2. Background

Farmer herder conflict in Nigeria

The Farmer-Herder conflict in Nigeria is primarily between farmers and herders and it stems from competition for increasingly scarce land resources. The conflict predates the country's independence in 1960 and it is still ongoing. Moreover, the conflict is seasonal, and it typically begins when herders migrate southwards from their settlement in the north to graze their cattle and it peaks in January (ACLED 2022) around the main harvest season period (FEWSNET 2020). This period is characterized by high temperatures, low humidity and sparse vegetation in the Northern region of the country. Hence, herders migrate to the North Central region and the farther southern part of the country which are characterized by longer rainy season period, high humidity, and dense vegetation to feed their livestock.

Prior to 2010, during the early stage of the conflict, conflict incidences typically occurred in the north central region of the country with few isolated events in other parts of the country (ACLED 2022). During this period, low conflict frequency and severity were reported. However, after 2010, the farmer herder conflict incidence increased significantly, and it has been growing steadily. By 2016, over 80% of the 36 states in Nigeria have experienced at least one Farmer-Herder conflict event. The Farmer-Herder conflict led to 1,300 fatalities in 2018, surpassing the death toll from Boko Haram Conflict in the same year (ACLED 2022).

While Farmer-Herder conflict events are primarily driven by competition over land resources, several factors also contribute to conflict incidence. These factors are interconnected, mutually reinforcing each other. Climate change is a contributing factor to the increased competition over water and land resources between farmers and herders (George et al. 2021; FAO 2012; Kima et al, 2015; Adano et al. 2012; Buhaug et al. 2015; Theisen 2012; Hendrix and

Salehyan 2012). According to the Federal Ministry of Environment (2012), lower level of precipitation has led to desertification in the Northern region of Nigeria where most Fulani herders resides.

Due to these unfavorable climatic conditions in the northern part of Nigeria more Fulani herders are migrating farther southwards and staying for longer periods in host communities (ICG 2017; Benjaminsen et al. 2012; Buhaug et al., 2015; and Eke 2020) The depletion of water within Lake Chad, which is a major water source for herders, is also a contributing factor to the changes in the migratory pattern of Fulani Herders (Oli et al 2018; Njoku et al, 2018). This change in the migratory pattern has led to Fulani Herders migrating to agrarian communities that are not used to hosting them in the past which results in increased tension and violence.

Another major source of the escalation of the Farmer-Herder conflict is Nigeria's rapid population growth. Nigeria is the most populous country in Africa with a population of over 213 million and annual population growth rate of 2.4% in 2021 (World Bank 2023). Between 2010 and 2020, Nigeria population grew by about 30% (World Bank 2023) and population forecast shows that the country's population would almost double the current total population by 2050 (Statista 2023). This has led to an increased demand for land for food production to feed the growing population and for residential and industrial purposes.

In 1965, the Federal government established grazing corridors for herders to graze their cattle. However, this land has been re-assigned for other land use purposes due to ineffective policy implementation (Ojo 2020). Only a small fraction of the grazing corridors established in 1965 is currently available to herders for grazing (ICG 2017).The implementation of government policies that negatively affect Fulani Herders' interests (Benjaminsen and Ba 2009; Mertz, Rasmussen, and Rasmussen 2016) and reassign previously established grazing corridors (Seter, Theisen, and Schilling 2018; Lenshie et al. 2020) and grazing land resources (Clanet and Ogilvie 2009) for other land use purposes further exacerbates the situation.

Due to technological advancement, there has been a shift in the balance of mutual interest between herders and farmers. In the past, when herders migrated to host communities their cattle were allowed to graze on crop fodder left on farmlands and in return, the animal waste from the cattle are used to fertilize the farmlands. Further, the cattle provide dairy products to farmers in host communities. However, technological development has made chemical fertilizers and various forms of shelf stable dairy products available to farmers in host communities.

Changes in the demographic characteristics of stakeholders in the Farmer-Herder conflict context have led to the prevalence of violence and poor conflict resolution outcomes. There seems to be a trend among cattle owners to employ young herders who are less tolerant than their older counterparts (ICG, 2017). Further, more young farmers are engaging in farming activities, and they are less tolerant to grazing activities (Usman and Nichol 2022).

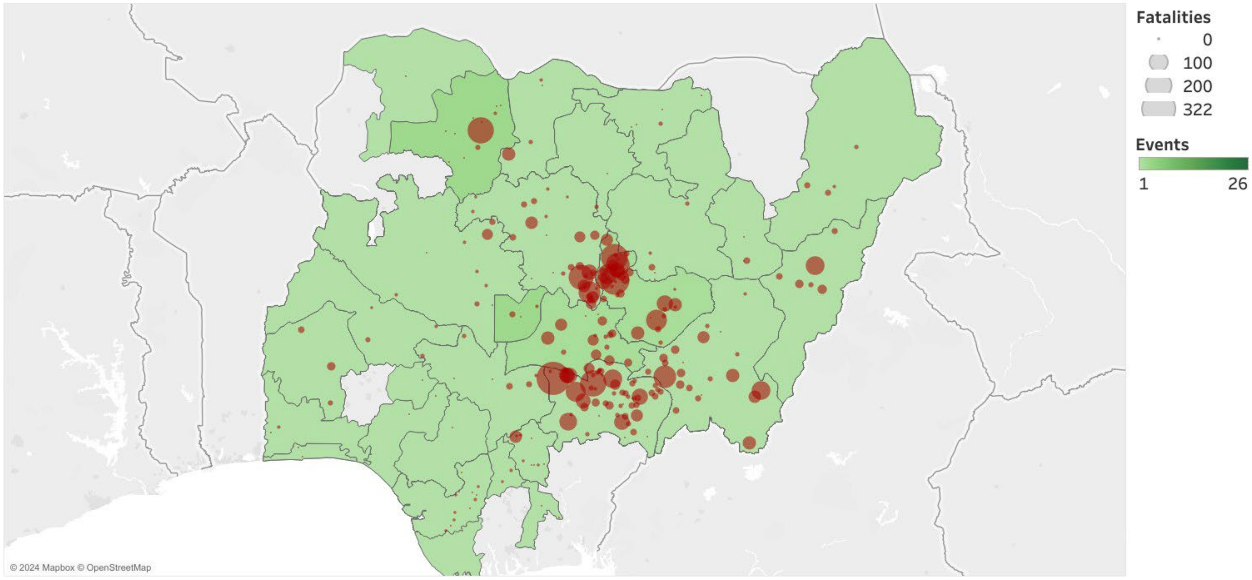
Lastly, other forms of violence at the regional and national level have contributed to the exacerbation of the Farmer-Herder conflict. Cattle rustling in the north central part of the country has become increasingly rampant ICG (2017) and has led to substantial loss of cattle and fatalities among herders. Hence, Fulani herders carry firearms during their grazing activities to protect themselves and their livestock which further increases violence in host communities. At the national level, the Boko-Haram conflict is rampant in the northern part of the country which causes Fulani herders to further migrate south and stay longer in host communities to avoid the Boko-Haram militants (George et al., 2021). Another channel through which the Boko-Haram conflict facilitates Farmer-Herder conflict is through an increase in the availability of, and access to, firearms in the country.

Seasonality of Farmer-Herder conflict events and agricultural production in Nigeria

Figure 2.1 shows the spatial distribution of the Farmer-Herder conflict events from 2010 to 2016. The Farmer-Herder conflict could affect agricultural productivity through various factors of production at different phases of the agricultural cycle. The planting period in the northern region of Nigeria is usually from May to mid-June, while in the southern region, it is from mid-March to April (FEWSNET 2023). This period is characterized by relatively high Farmer-Herder conflict incidence and fatalities (ACLED 2022).

Farmer-Herder conflict occurrence during the planting season could be especially debilitating. Farm households affected could lose labor force critical for crop production due to fatalities or injury incurred during the period. Apart from fatalities, destruction of household assets and farm inventories are often reported as consequences of Farmer-Herder conflicts. Affected farm households may be unable to purchase sufficient inputs due to loss of assets or supply sufficient household labor for land preparation and cultivation. Shortages of labor could drive up hiring wages. Hence, farm households could potentially incur higher cost of inputs.

Figure 2.1: Spatial variation in the Farmer-Herder Conflict Events (2010 – 2016)



Source: ACLED(2023).

The pre-harvest season period is not as labor intensive as the planting period. Conflict occurrences during the pre-harvest period could also be detrimental if they result in the destruction of crops. Apart from the cost incurred in replanting crops, farmers may be unable to successfully re-cultivate as the crops may not flower in the appropriate time frame which consequently leads to loss of agricultural output. The pre-harvest period in the northern region of Nigeria is typically from July to September while in the southern part of the country, the pre-harvest period is from May to August (FEWSNET 2023). The number of conflict incidences and fatalities during this period are relatively lower compared to conflict events during the planting season.

The harvest period in the northern part of the country is from September to December (FEWSNET 2023). While the southern part of the country may harvest certain crops like cassava all year round, the main harvest period in this region is from September to November

(FEWSNET 2023). Farmer-Herder conflict incidence is typically at its lowest during this period (ACLED 2022).

However, conflict incidence during the harvest period may also be catastrophic if it results in the destruction of crops and affects labor available for harvest activities. Further, if conflict during this period affects farmers' access to markets, it could result in post-harvest loss due to spoilage and lower income due to higher transaction costs. On the other hand, the impact of conflict during this period may be minimal for farm households that harvested and sold their farm produce earlier in the harvest period. Table 2.1 below shows the typical timing of each agricultural phase in the northern and southern region of Nigeria.

Table 2.1: Agricultural cycle in the Northern and Southern region of Nigeria

Agricultural phase	Northern region	Sothern region
Land preparation	February - May	February - mid-March
Planting	May - mid-June	mid-March - May
Pre-Harvest	July - August	May - August
Harvest[9]	September - January	September - December

FEWSNET (2023)

[9] There is an off-season harvest period in the northern region from April to June. In the southern region, the green harvest season when maize and yam are harvested in from mid-May to September while cassava harvest is done all year round.

2.3. Data

The study uses the Nigeria GHSP (General Household Survey Panel) dataset and the Armed Conflict Location and Event Dataset (ACLED). The Nigeria GHSP is part of the World Bank's LSMS (Living Standard Measurement Survey) and the survey was conducted by the Nigeria Bureau of Statistics (NBS). The Nigeria GHSP datasets consist of four survey waves, which are: 2010/2011, 2012/2013, 2015/2016, and 2018/2019 survey. There was a refresh of households surveyed in the 2018/2019 wave which consequently lead to the 2018/2019 dataset containing only a subsample of the households that are present in the original GHSP 2010/2011 datasets. Further, to ensure the safety of the enumerators, areas undergoing conflict during the period of the GHSP 2018/19 survey were not surveyed. Thus, this study only utilizes datasets from the Nigeria GHSP 2010/11, 2012/13, and 2015/16 waves.

The Nigeria GHSP survey is conducted on a nationally representative sample selected through a two-phase stratified sampling technique. In the initial phase, primary sampling units called "enumeration areas" were chosen from each state. The probability of selecting an enumeration area was proportional to its size, determined by the total number of enumeration areas in each state and the total households listed in those enumeration areas. This ensured enumeration areas with more households had a higher chance of being selected. In the second phase, ten households were systematically selected from the list of households in each chosen enumeration area.

The GHSP dataset includes information on quantity of crop harvested by farm households, price and quantity of crop sold, price and quantity of farm inputs purchased by households, household demographic and farm characteristics, weather factors, and household location geo-coordinates. ACLED collects information on farmer-herder conflicts from 1997 to

2023. In addition, ACLED gathers data from newspapers, reports, and other media sources to provide details on the conflict events including the number of fatalities, type of conflict, conflict event date, conflict actors, and conflict location geo-coordinates. The study uses conflict events information from the ACLED dataset for the years household datasets are available, in this instance, from 2010 to 2011, 2012 to 2013, and from 2015 to 2016.

In addition, to better identify conflict events that have an impact on crop income, our study focused on the period extending from the commencement of planting to the conclusion of harvesting. Nevertheless, there is a lack of data regarding the termination of the harvesting season for the 2010/2011 and 2012/2013 planting cycles. Hence, we utilized the harvest completion dates reported by farmers in the 2015/2016 cycle as a proxy for the earlier 2010/2011 and 2012/2013 cycles.

Table 2.2 displays the list of variables used in the study and their description. The dependent variables include crop income which is used in the main regression analysis. Value of crop production, inorganic fertilizer cost, organic fertilizer cost, work animal rent, machinery rent, labor cost and seed costs are dependent variables used in assessing the mechanisms through which conflict affects crop income.

To ensure consistency in our analysis, the crop income and other dependent variables used to assess the pathways through which conflict impacts crop income are converted from the Nigeria currency, Naira, to 2022 USD purchasing power parity (PPP) using the World Bank PPP conversion factor. First, we adjusted for inflation using World Bank data on annual CPI in Nigeria for the relevant survey years (2010/11, 2012/13, and 2015/16). To do this, we calculated the inflation rate for each survey wave by subtracting the survey year's CPI from the 2022 CPI and dividing the result by the survey year's CPI. We then applied this inflation rate to the Naira value, adding the original Naira value to the result obtained. Finally, we divided the inflation adjusted value by the 2022 USD PPP.

Table 2.2: Data description of variables used in the study.

Variable	Description
Dependent variables	
Crop income[10]	Is the net crop income. It is constructed by deducting the total input costs[11] from the total value of crop production.
Value of Crop Production[12]	Is the gross value of crop production across all crops and seasons.
Inorganic fertilizer expenditure	Is the total expenditure household incurred in the purchase of fertilizer by household.
Organic fertilizer expenditure	Is the total expenditure household incurred in the purchase and the transportation of purchased organic fertilizer.
Work animal rent	Is the cost incurred by household in renting work animal and feeding animal rented
Pesticide expenditure	Is the cost incurred in the purchase of pesticides by household.
Machinery rent	Is the cost incurred in renting machinery or equipment's by household.
Labor expenditure	Is the total hired labor cost incurred by household. It is constructed using the daily wage per worker multiplied by the number of laborers hired plus the value of the amount of crops given as payment

[10] Crop income is winsorized at top 1% to remove outliers.

[11] The input costs are expenditures on fertilizer, seeds, labor, pesticides, land rent, work animal rent, and machinery rent.

[12] It is the gross value of crop production across all crops and seasons without taking into consideration post-harvest losses. The valuation of crop production followed a two-step process. First, a respondent's own crop valuation was utilized when provided. Otherwise, the total quantity harvested for each crop was multiplied by the sales price per unit based on transactions observed for households selling that particular crop. For any crops that were not sold by the surveyed household, a per-unit imputed value was calculated. This was derived from the median kilogram sales values of that crop using observed sales data from a minimum of 10 transactions in Nigeria. The value of crop production is winsorized at top 1% to remove outliers.

Seed expenditure	Is the total expenditure household incurred in seed purchase and the transportation of purchased seed.
Independent variables	
Conflict Events (10km radius)	Is a continuous variable that measures the number of conflict events within 10km radius of each household.
Household Head's Age	The age of household head in years
Female Household Head	Is a binary variable that takes the value of 1 if household head is female and "0" if otherwise
Age Dependency Ratio	Is the ratio of household members under 15 and over the age of 65 to the household members aged 15 - 64
Household size	Is the total number of household members in the household
Household Distance to Administrative Center (km)	Is the distance from household residence to the capital of household's state of residence in kilometers
Household Distance to Market (km)	Is the distance from household residence to the nearest market in kilometers
Household Distance to Nearest Major Road (km)	Is the distance from household residence to the nearest major road in kilometers
Household Distance to Nearest Border Crossing (km)	Is the distance from household residence to the nearest border crossing in kilometers
Land size in hectares	Is household land size in hectares
Rural household	Is a binary variable that takes the value of 1 if household is located in a rural area and "0" if otherwise
Land slope (percent)	Slope of household land in percent
Annual Mean Temperature (C * 10)	Annual mean temperature in degree Celsius multiplied by 10
Average 12-month total rainfall(mm)	Average 12-month total rainfall in mm from January to December
Average EVI value at peak of greenness within growing season	Average EVI value at peak of greenness within growing season
Fatal conflict exposure	Is a binary variable that takes the value of "1" if household is within 25km of at least one fatal conflict event and "0" if otherwise.
Number of conflict events	Is the total number of conflict events that occur within 25km radius of a household location.

Table 2.3 provides an overview of the variables utilized in the study's main regression analysis. The study reveals that households, on average, earned US$1,282.61 as crop income. Most of the households are headed by males and consist of smallholder farmers who possess an average farm size of approximately 2 hectares. Further, a relatively small percentage of households in the study reside in urban areas. The average distance between household and the nearest border crossing is only about 10km. However, the average distance between households in the study and the nearest administrative center, major road, and market center is substantial. This suggests that, on average, households in the sample are located in remote areas.

Table 2.3: Descriptive statistics of variables

Variable	Observation	Mean	Std. Dev.	Min	Max
Dependent variable					
Crop income	6,743	1282.61	2063.01	-3339.81	13172.39
Value of Crop Production	6,743	1841.81	2609.43	0	23055.64
Inorganic fertilizer expenditure	6,743	72.23	161.26	0	1017.94
Organic fertilizer expenditure	6,743	17.11	59.01	0	608.12
Work animal rent	6,743	27.46	77.96	0	634.56
Pesticide expenditure	6,743	11.89	34.13	0	264.40
Machinery rent	6,743	3.80	28.34	0	264.40
Labor expenditure	6,743	295.87	692.40	0	4944.27
Seed expenditure	6,743	18.71	53.92	0	423.04
Independent variables					
Conflict events (10km radius)	6,743	0.03	0.38	0	10
Land slope (percent)	6,743	2.68	2.57	0.00	40.40
Age dependency ratio	6,743	1.25	0.85	0.08	11
Household size	6,743	7.56	3.25	1	33
Female household head	6,743	0.10	0.30	0	1
Household head age	6,743	51.33	14.44	17	108
Household Distance to Administrative Center (km)	6,743	78.12	54.55	0.20	309.00
Household Distance to Market (km)	6,743	69.77	38.94	0.40	214.36
Household Distance to Nearest Major Road (km)	6,743	10.66	13.53	0	115.20
Household Distance to Nearest Border Crossing (km)	6,743	309.68	188.13	1.60	671.80
Land size in hectares	6,743	1.90	2.80	0	17.69
Rural household	6,743	0.90	0.31	0	1
Annual Mean Temperature (C * 10)	6,743	26.40	0.99	21.00	28.80
Average 12-month total rainfall(mm)	6,743	1220.32	458.19	431	2574

Average EVI at peak of greenness within growing season	6,743	0.45	0.04	0.38	0.59

2.4. Identification strategy

The study uses a panel fixed effects model, which exploits the spatial and temporal variation in the Farmer-Herder conflict events to analyze the impact of conflict on crop income. A potential source of bias in our study is omitted variable bias. Herders may choose to graze on household farmland due to household characteristics or the characteristics of the local government areas in which they are located.

In addition, households may be selected into conflict based on household characteristics that are unobserved. Hence, we included household and Local Government Area (LGA) fixed effects in our model to account for time invariant unobserved heterogeneity at the household and LGA level in our analysis. We also included some household variables in our model to control for time varying unobserved heterogeneity at the household level.

Further, some states may be more prone to Farmer-Herder conflict due to their proximity to herders' settlements, ease of access to grazing lands or some other ethnic, geographical, or climatic factors. State policies banning open-grazing are one of the time-varying factors which are known to provoke or exacerbate Farmer-Herder conflict events. Hence, we included a state-specific time trend variable to control for this and other time varying unobserved heterogeneity at the state level in our model. Further, we included a survey wave fixed effects to account for unobserved heterogeneity that are specific to each survey wave period.

Empirical model

A panel fixed effects model was used to analyze the research objectives. The outcome variable for the main research objective is crop income. We used the following outcome variables to assess the pathways through which conflict affects crop income: value of crop production, fertilizer expenditure, pesticide expenditure, herbicide expenditure, work animal rent, machinery rent, hired labor expenditure, and seed expenditure.

The equation below depicts the model used to analyze the study's research objectives.

$$Y_{ijt} = \alpha + \beta_1 Conflict\ Events_{ijkt} + \gamma X_{ijkt} + \theta_i + \omega_t + \mu_j + \delta_k \tau_{kt} + \varepsilon_{ijkt} \qquad (1)$$

Where:

Y_{ijkt} is the outcome variable of household i in LGA j in state k at time t.

$Conflict\ Events_{ijkt}$ is the number of conflict events within 10km radius of household i in LGA j in state k at time t.

X_{ijkt} is a vector of household level characteristics.

θ_i is household fixed effect.

ω_t is survey round fixed effect.

μ_j is LGA fixed effect.

$\delta_k \tau_{kt}$ is the state-specific time trend.

ε_{ijkt} is the idiosyncratic error term.

The model depicted in equation (2) below is used to analyze the heterogeneity in impact of conflict exposure by month of conflict occurrence.

$$Y_{ijt} = \alpha + \beta_1 Conflict_{ijkt} * m + \gamma X_{ijkt} + \theta_i + \omega_t + \mu_j + \delta_k \tau_{kt} + \varepsilon_{ijkt} \qquad (2)$$

Where :

$Conflict_{ijkt}$ is a dummy variable that takes the value of 1 if household i in LGA j at time t in state k is within 10km radius of a conflict event and 0 if otherwise.

m is a dummy variable for the month of conflict occurrence.

2.5. Results

Table 2.4 displays the panel fixed effects estimates for the impact of conflict on crop income for farm households within 10km of conflict locations. The first column reports the baseline model with household and survey wave fixed effects. Findings reveal that conflict has a negative but statistically insignificant impact on crop income. Control variables, including household socio-economic and demographic characteristics, are added to the baseline model and reported in the second column. Further, we included the LGA fixed effect in the fourth column. Results show that with the inclusion of control variables and the LGA fixed effects in the third and fourth columns, the impact of conflict on crop income becomes positive yet statistically insignificant.

In the fifth column, the state-specific time trend variable was included, while the time-trend variable, in addition to the LGA fixed effects, was introduced to the model reported in the last column. Estimates reported in the last two columns are consistent with that reported in the first column, i.e., conflict has a negative but no statistically significant impact on crop income. The model presented in the last column of the table is our preferred model.

Among the control variables used in the analysis, household distance to the nearest major road, household age dependency ratio, and having a female household head have a negative and statistically significant impact on crop income. In contrast, household farm size has a positive effect on crop income. Results reveal that for each kilometer a household is farther from the nearest major road, their crop income decreases by about US$6. Access to roads is vital to crop income as it improves agricultural productivity (Gebresilasse, 2022; Shamdasani, 2021) by facilitating farmers' access to vital input and output markets and extension services.

Further, farm household crop income rises by approximately US$52 for each hectare of land owned by the farm household. In other words, farm households earn about 4% of the average crop income in the sample for each hectare of land they possess. This finding is corroborated by studies (Foster & Rosenzweig, 2022; Omotilewa et al., 2021), who found that larger farm sizes have a positive impact on farm productivity.

On average, female-headed households earn about 26% less than male-headed households. This finding is supported by studies that found that females earn lower crop income than their male counterparts due to gender disparities in access to resources and constraints to asset ownership (Olorunsanya & Omotesho, 2011; Takane, 2007) and decision-making power (Debela & Abebe, 2017).

Table 2.4: Effect of Conflict on Crop Income within 10km Exposure Radius

	Model 1	Model 2	Model 3	Model 4	Model 5
Conflict events (10km)	-51.998	25.751	34.032	-69.170	-58.063
	(83.147)	(302.609)	(303.522)	(265.240)	(266.217)
Land slope (percent)		22.461	4.085	-4.079	-20.237
		(43.259)	(42.115)	(42.520)	(44.574)
Age dependency ratio		**-97.358****	**-94.121****	**-113.543*****	**-110.235****
		(45.719)	**(45.797)**	**(42.767)**	**(42.922)**
Household Size		5.795	-3.530	25.440	17.798
		(33.918)	(33.809)	(32.011)	(31.799)
Female household head		-266.815	-270.904	**-327.106***	**-338.741***
		(194.919)	(196.699)	**(182.560)**	**(183.994)**
Household head's age		26.959	26.909	21.491	21.393
		(22.196)	(22.361)	(20.829)	(20.979)
Household head's age squared		-0.281	-0.288	-0.232	-0.238
		(0.191)	(0.192)	(0.181)	(0.182)
Household distance to administrative center (km)		-1.741	-2.292	-1.535	-2.872
		(2.849)	(2.792)	(3.171)	(3.034)
Household distance to market (km)		-17.299	13.474	-17.416	20.776
		(16.226)	(22.525)	(15.988)	(21.223)
Household distance to nearest major road (km)		**-4.909***	**-4.773***	**-6.255****	**-6.472****
		(2.511)	**(2.566)**	**(2.638)**	**(2.643)**
Household distance to nearest border crossing (km)		2.290	2.780	-0.635	0.147
		(2.279)	(2.427)	(2.449)	(2.384)
Land size in hectares		**76.008*****	**76.906*****	**52.056*****	**52.380*****
		(15.060)	**(15.092)**	**(14.256)**	**(14.283)**
Rural households		233.614	17.355	419.533	240.589
		(990.197)	(444.499)	(932.021)	(383.011)
Annual mean temperature		-348.103	-338.475	-331.257	-287.168
		(360.801)	(268.617)	(376.366)	(269.123)
Average 12-month total rainfall(mm)		-2.042	-1.485	0.804	2.335
		(1.932)	(1.879)	(2.429)	(2.191)
Average EVI value at peak of greenness within growing season		1058.851	2608.685	-4177.892	343.685
		(4536.520)	(3986.315)	(6014.327)	(5065.006)
Constant	933.918***	11944.892	8391.470	12303.814	4713.487
	(24.478)	(11713.96)	(9206.601)	(12996.38)	(9720.134)
Household fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Survey wave fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
LGA fixed effects	*No*	*No*	*Yes*	*No*	*Yes*
State-specific time trend	*No*	*No*	*No*	*Yes*	*Yes*
R-squared within	0.042	0.064	0.074	0.194	0.204
R-squared overall	0.019	0.005	0.049	0.002	0.002
Observations	8367	6743	6743	6743	6743

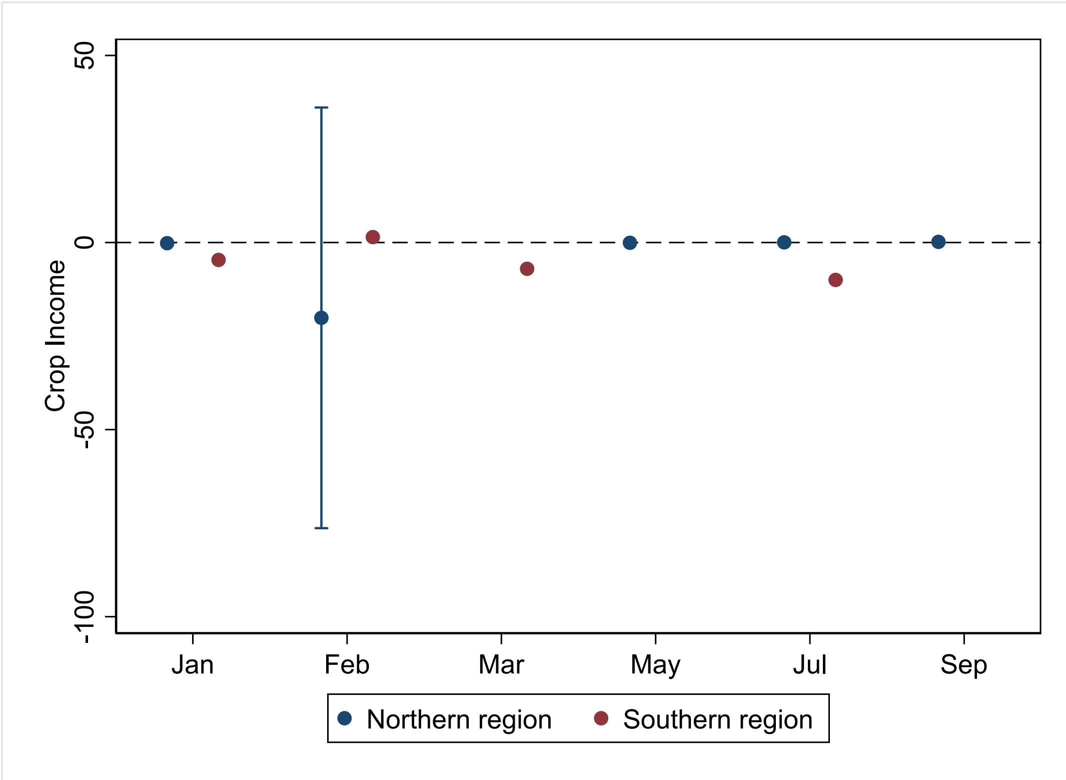
Standard errors robust to heteroskedasticity are reported in parenthesis. The dependent variable is *Crop income* which is the value of crop production less total explicit input expenditure. The variable of interest is Conflict events which is a continuous variable that measures the number of conflict event within 10km radius of a conflict location. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria GHSP and ACLED.

Heterogeneity in the impact of conflict

In this section, we attempt to evaluate whether there is heterogeneity in the impact of conflict on crop income in each phase of the agricultural cycle. It is important to note that the southern and northern regions of the country observe each phase of the agricultural cycle at different times of the year. Hence, we assessed the heterogeneity in the impact of conflict separately for each region, as shown in Figure 2.2.

The variability in conflict exposure by month within a 10km exposure radius is minimal. As a result, we assessed the heterogeneity in the impact of conflict within a 25km exposure radius. The findings indicate no statistically significant differential impact of conflict on crop income across different months.

Figure 2.2: Heterogeneity in the impact of conflict on crop income by month and region



Standard errors are robust to heteroskedasticity. The dependent variable is *Crop income*[13]. The main variable of interest is *Monthly conflict exposure,* a categorical variable, assigns values from 1 to 12 to a household if it's within 25 kilometers of a conflict event, with each number corresponding to a month from January (1) to December (12). The baseline is August (8). Control variables include *plot slope in percent, age dependency ratio, household size, household head age, gender of household head, household distance to capital of state of residence (km), household distance to nearest market (km), household distance to nearest major road (km), household distance to nearest border crossing (km), household land size in hectares, rural household, annual mean temperature, average 12 months total rainfall (mm), average EVI value at peak of greenness within growing season*.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria GHSP and ACLED.

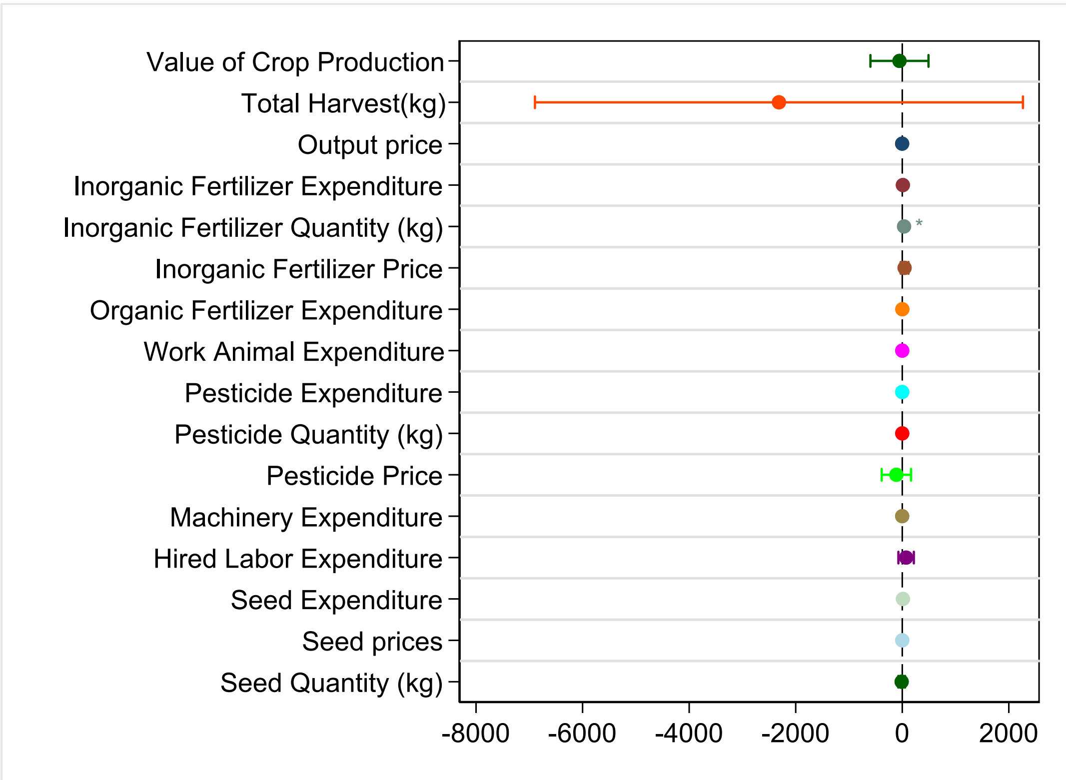
The impact of conflicts on components of crop income

In this section, we analyzed the impact of conflict on the variables used in constructing crop income in the study. The estimates obtained from the analysis are reported in Figure 2.3 below. Although findings show that conflict has a negative impact on the value of crop production and a

[13] The crop income data is normalized using a min-max normalization method.

positive impact on fertilizer, seed, and hired labor expenditure. However, none of these effects are statistically significant, except for the impact of conflict on quantity of inorganic fertilizer.

Figure 2.3: Mechanism of conflict impact on crop income

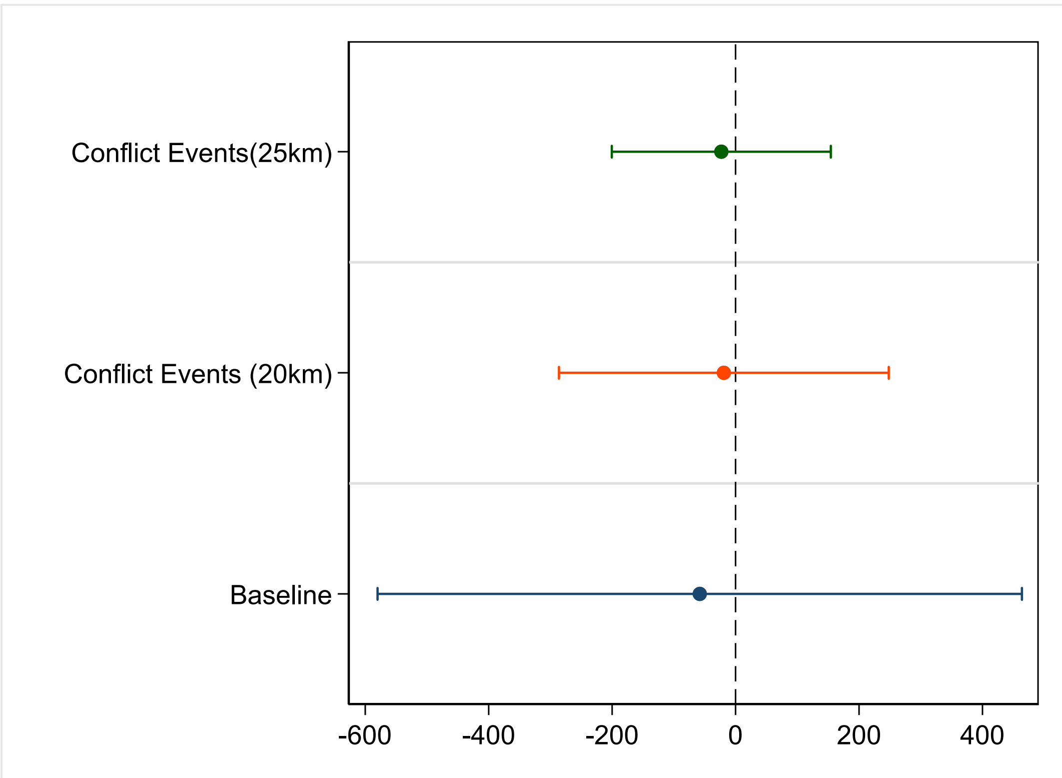


Standard errors are robust to heteroskedasticity. The dependent variables include *Value of crop production, Inorganic fertilizer expenditure, Organic fertilizer expenditure, Draft animal rent, Pesticide expenditure, Machinery rent, Labor expenditure Seed expenditure, Seed price and Seed Quantity*. The main variable of interest is *Conflict events* which measure the number of conflict events within 10 km radius of each household. Control variables include *plot slope in percent, age dependency ratio, household size, household head age, gender of household head, household distance to capital of state of residence (km), household distance to nearest market (km), household distance to nearest major road (km), household distance to nearest border crossing (km), household land size in hectares, rural household, annual mean temperature, average 12 months total rainfall (mm), average EVI value at peak of greenness within growing season*.* p < 0.10, ** p < 0.05, *** p < 0.01. Source: Nigeria GHSP and ACLED.

Robustness check

Figure 2.4 reveals the estimates of the impact of conflict on crop income using different conflict measures. We substitute conflict events within a 10km radius in our baseline model for each conflict measure: conflict events within a 20km radius and conflict events within a 25km radius. Our findings remain consistent with the substitution of alternative conflict measures. Table B.1 in the appendix section reports findings from the impact of conflict on crop income using a balanced panel. The result is consistent with the findings reported in Table 2.4, albeit the estimated magnitudes are substantially larger.

Figure 2.4: Robustness checks on the impact of conflict on crop income



Standard errors are robust to heteroskedasticity. The dependent variable is *Crop income*. The main variables of interest are *Conflict events (10km), Conflict events (20km), Conflict events (25km). Conflict events (10km), Conflict events (20km),* and *Conflict events (25km)* measure the number of conflict events within 10km, 20km, 25km radius of each household, respectively. The baseline is *Conflict events (10km*Control variables include *plot slope in percent, age dependency ratio, household size, household head age, gender of household head, household distance to capital of state of residence (km), household distance to nearest market (km), household distance to nearest major road (km), household distance to nearest border crossing (km), household land size in hectares, rural household, annual mean temperature, average 12 months total rainfall (mm), average EVI value at peak of greenness within growing season*.* p < 0.10, ** p < 0.05, *** p < 0.01. Source: Nigeria GHSP and ACLED.

Conclusion

In this study, we provide robust evidence that Farmer-Herder conflicts have no statistically significant impact on crop income in Nigeria. The negative effect persists with the inclusion of LGA fixed effects and state-specific time trends. However, we found that while conflict has no statistically significant impact on crop income overall, it has a positive impact on the quantity of fertilizer purchased.

Further, results show that household access to roads and household agricultural land size are important determinants of household crop income. This finding emphasizes the crucial role of accessible infrastructure in agricultural productivity. Roads are vital in connecting farmers to larger markets, facilitating the transport of goods, and ensuring timely access to agricultural inputs and services.

One key recommendation is prioritizing infrastructure development in rural areas, particularly road construction and maintenance. Improving road connectivity can substantially boost agricultural productivity by reducing transportation costs and increasing market accessibility for farm produce. In addition, policies should be geared towards supporting land acquisition and consolidation for smallholder farmers, especially female farmers. This could involve facilitating access to land through lease or purchase and providing incentives for land pooling among smallholders.

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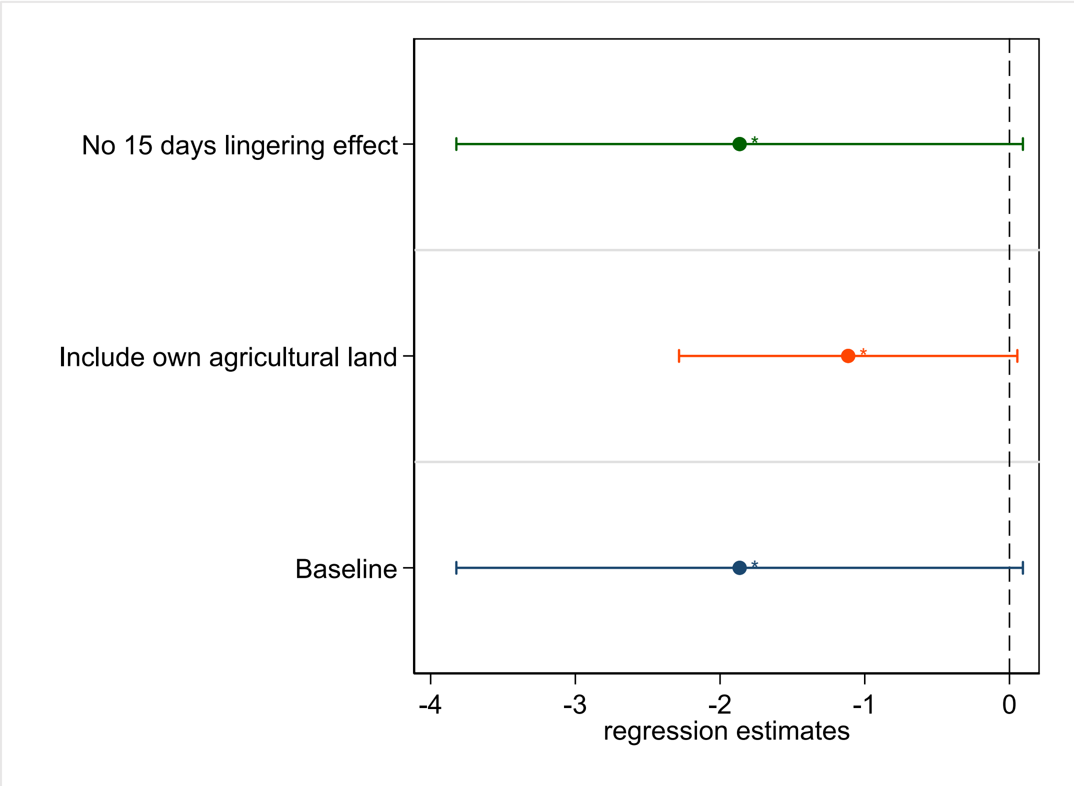
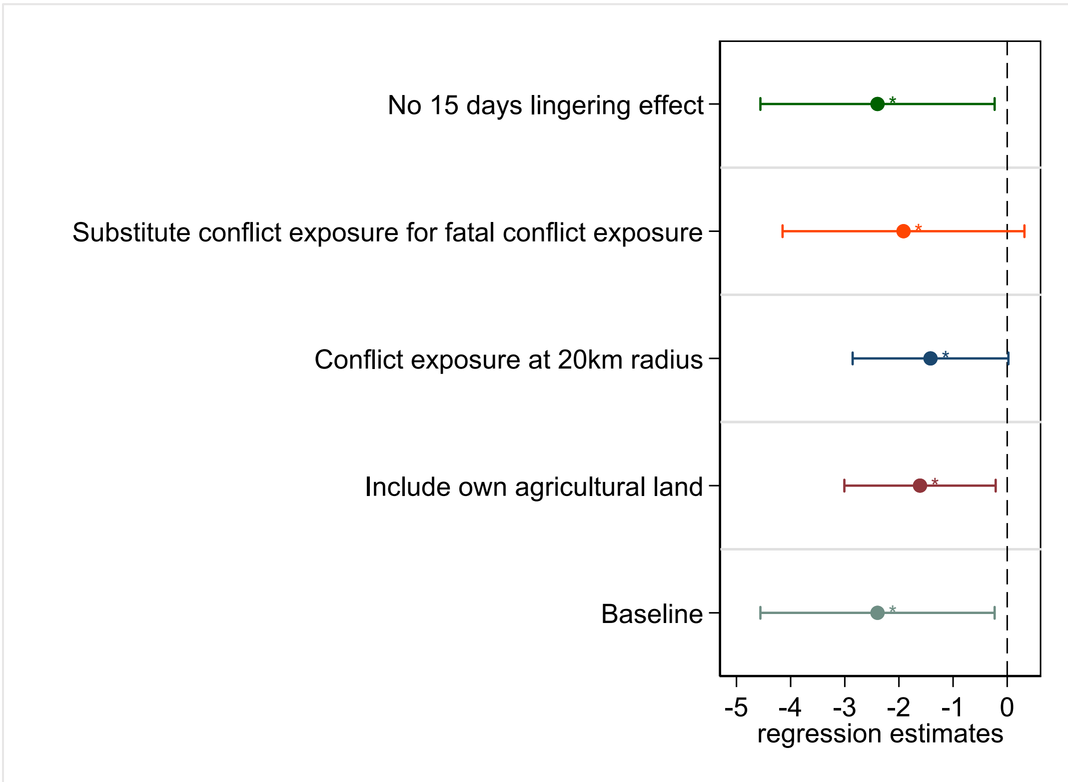
Appendix A - Appendix for Chapter 1

Figure A.1 : Robustness check for the effect of conflict on children's Weight-for-Age Z-score



Robust standard errors are clustered at the household cluster level. The dependent variable is Weight-for-Age Z score. The graph illustrates the coefficient estimate based on a triple-difference analysis, denoted as the interaction term of the following variables: *Exposed cluster*, *Alive during conflict and Farm household*. *Exposed cluster* is the *Treatment* variable that takes the value of "1" if cluster is within 10km radius of at least one conflict event from August 2017 to the time of household survey (Nigeria DHS 2018 survey was conducted from August 2018 to December 2018) and "0" if otherwise. *Alive during conflict* is the *Post* variable that takes the value of "1" if a child was alive during conflict and "0" if the child was born after conflict ended in their cluster. *Farm household* is a dummy variable that takes the value of "1" if a household head or their spouse is engaged in agricultural occupation and "0" if otherwise. Other independent variables used includes child's age in months, child's gender, child's birth order, household head age, household head gender, household head years of education, household size, number of children in the household, mother's education level, and number of conflict events within 20km radius of the cluster from August 2017 to the time of household survey. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS and ACLED

Figure A.2: Robustness check for the effect of conflict on children Height-for-Age Z-score



Robust standard errors are clustered at the household cluster level. The dependent variable is Height-for-Age Z score, The graph illustrates the coefficient estimate based on a triple-difference analysis, denoted as the interaction term of the following variables: *Exposed cluster*, *Alive during conflict and Farm household*. *Exposed cluster* is the *Treatment* variable that takes the value of "1" if cluster is within 10km radius of at least one conflict event from August 2017 to the time of household survey (Nigeria DHS 2018 survey was conducted from August 2018 to December 2018) and "0" if otherwise. *Alive during conflict* is the *Post* variable that takes the value of "1" if a child was alive during conflict and "0" if the child was born after conflict ended in their cluster. *Farm household* is a dummy variable that takes the value of "1" if a household head or their spouse is engaged in agricultural occupation and "0" if otherwise. Other independent variables used includes child's age in months, child's gender, child's birth order, household head age, household head gender, household head years of education, household size, number of children in the household, mother's education level, and number of conflict events within 20km radius of the cluster from August 2017 to the time of household survey. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS and ACLED

Table A.1: The impact of conflict on children's nutritional and health outcomes of children born between August 2017 and 2018

	WAZ	HAZ
Alive during conflict	-0.118	-0.210
	(0.667)	(0.744)
Conflict exposure (10km)	0.349	0.123
	(0.414)	(0.429)
Alive during conflict * Conflict exposure	-0.026	-0.111
	(0.645)	(0.608)
Farm household	-1.629	-2.890*
	(1.361)	(1.477)
Alive during conflict * Farm household	1.175	1.762
	(1.308)	(1.654)
Conflict exposure * Farm household	1.510	1.940
	(1.266)	(1.557)
Alive during conflict * Farm household * Farm household	**-3.149****	**-3.013***
	(1.571)	**(1.791)**
Constant	-1.268	-2.438*
	(1.505)	(1.394)
Controls	*Yes*	*Yes*
Child year of birth fixed effect	*Yes*	*Yes*
R-squared	0.142	0.171
Number of children	144	144

Robust standard errors clustered at the household cluster level are reported in parenthesis. The dependent variables are Weight-for-Age Z score and Height-for-Age Z score. The variables of interest are *Conflict exposure*, *Alive during conflict, and Farm household*. *Conflict exposure* is the *Treatment* variable that takes the value of "1" if cluster is within 10km radius of at least one conflict event from August 2017 to the time of household survey (Nigeria DHS 2018 survey was conducted from August 2018 to December 2018) and "0" if otherwise. *Alive during conflict* is the *Post* variable that takes the value of "1" if a child was alive during conflict and "0" if the child was born after conflict ended in their cluster. *Farm household* is a dummy variable that takes the value of "1" if a household's head or their spouse are engaged in agriculture and "0" otherwise. Other independent variables used include child's age in months, child's gender, household head age, household head gender, household head years of education, household size and number of children in the household. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS and ACLED

Table A.2: The impact of conflict on children's dietary diversity score

	MDDS	MDDS	MDDS
Conflict exposure	-0.102	-0.122	-0.102
	(0.304)	(0.323)	(0.304)
Farm household	**1.470****	0.856	**1.470****
	(0.608)	(0.588)	**(0.608)**
Conflict exposure *Farm household	**1.382****	**1.093****	**1.382****
	(0.563)	**(0.505)**	**(0.563)**
Constant	1.083	1.622	1.083
	(3.015)	(3.178)	(3.015)
Controls	*Yes*	*Yes*	*Yes*
Birth order fixed effect	*No*	*Yes*	*No*
Month of interview fixed effect	*No*	*No*	*Yes*
R-squared	0.189	0.167	0.189
Number of children	397	395	397

Robust standard errors clustered at the household cluster level are reported in parenthesis. The dependent variable is Minimum Dietary Diversity Score. The variables of interest are *Conflict exposure and Farm household*. *Conflict exposure* is the *Treatment* variable that takes the value of "1" if cluster is within 10km radius of at least one conflict event from August 2017 to the time of household survey (Nigeria DHS 2018 survey was conducted from August 2018 to December 2018) and "0" if otherwise. *Farm household* is a dummy variable that takes the value of "1" if a household's head or their spouse are engaged in agriculture and "0" otherwise. Other independent variables used include child's age in months, child's gender, household head age, household head gender, household head years of education, household size and number of children in the household. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS and ACLED

Table A.3: The impact of conflict on child's medication intake

	Received vitamin A	Received vitamin A	Received anthelmi ntics	Received anthelmi ntics	Received iron pills	Received iron pills
Alive during conflict	0.379	0.368	0.224	0.201	0.230*	0.176
	(0.341)	(0.326)	(0.136)	(0.143)	(0.132)	(0.151)
Exposed cluster	0.205	0.181	-0.043	-0.047	-0.029	-0.050
	(0.364)	(0.376)	(0.124)	(0.130)	(0.141)	(0.141)
Alive during conflict * Exposed cluster	-0.159	-0.120	0.063	0.078	0.037	0.053
	(0.416)	(0.435)	(0.151)	(0.159)	(0.155)	(0.159)
Farm household	-0.109	-0.067	-0.220	-0.188	**-0.426****	**-0.448***
	(0.290)	(0.277)	(0.156)	(0.161)	**(0.209)**	**(0.251)**
Alive during conflict * Farm household	0.025	0.012	-0.102	-0.138	0.093	0.125
	(0.323)	(0.308)	(0.142)	(0.149)	(0.192)	(0.244)
Exposed cluster * Farm household	-0.472	-0.406	0.112	0.037	-0.181	-0.087
	(0.543)	(0.545)	(0.206)	(0.213)	(0.398)	(0.433)
Alive during conflict * Exposed cluster * Farm household	0.176	0.125	-0.071	0.034	-0.006	-0.068
	(0.509)	(0.534)	(0.209)	(0.219)	(0.325)	(0.365)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Birth order fixed effect	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Constant	1.519	2.174	0.271	0.413	-0.149	0.090
	(1.669)	(1.941)	(0.646)	(0.670)	(1.001)	(1.022)
R-squared	0.169	0.171	0.244	0.241	0.075	0.088
Number of children	399	398	399	398	399	398

Robust standard errors clustered at the household cluster level are reported in parenthesis. The dependent variables are Received vitamin A, Received anthelmintic, and Received iron pills, these are dummy variables that takes the value of 1 if a child received vitamin A, received medication for intestinal parasites, or received iron pills, respectively. The variables of interest are Exposed cluster, Alive during conflict, and Farm household. Exposed cluster is the Treatment variable that takes the value of "1" if cluster is within 10km radius of at least one conflict event from August 2017 to the time of household survey (Nigeria DHS 2018 survey was conducted from August 2018 to December 2018) and "0" if otherwise. Alive during conflict is the Post variable that takes the value of "1" if a child was alive during conflict and "0" if the child was born after conflict ended in their cluster. Farm household is a dummy variable that takes the value of "1" if a household's head or their spouse are engaged in agriculture and "0" otherwise. Other independent variables used include child's age in months, child's gender, household head age, household head gender, household head years of education, household size and number of children in the household. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS and ACLED

Table A.4: The impact of conflict on maternal access to healthcare

	Antenatal care facility	Antenatal care facility	Antenatal visits	Antenat al visits	Antenatal care provider	Antenatal care provider
Alive during conflict	-0.023	0.052	0.785	0.617	0.044	0.067
	(0.057)	(0.081)	(0.773)	(0.947)	(0.063)	(0.074)
Exposed cluster	-0.007	0.015	0.535	0.573	-0.002	0.000
	(0.073)	(0.095)	(0.925)	(1.072)	(0.059)	(0.067)
Alive during conflict * Exposed cluster	-0.022	-0.058	-1.137	-1.177	-0.061	-0.073
	(0.061)	(0.087)	(1.032)	(1.143)	(0.064)	(0.070)
Farm household	**-1.074*****	**-1.118*****	0.290	1.105	0.232	0.219
	(0.096)	**(0.097)**	(2.213)	(2.848)	(0.323)	(0.374)
Alive during conflict * Farm household	**1.017*****	**1.008*****	-1.406	-1.881	-0.074	-0.098
	(0.074)	**(0.087)**	(1.691)	(2.088)	(0.291)	(0.322)
Exposed cluster * Farm household	**1.014*****	**1.051*****	-0.473	-1.056	-0.187	-0.187
	(0.127)	**(0.136)**	(2.283)	(2.795)	(0.341)	(0.377)
Alive during conflict * Exposed cluster * Farm household	**-1.032*****	**-1.056*****	2.044	2.704	0.068	0.106
	(0.108)	**(0.138)**	(2.437)	(2.746)	(0.355)	(0.386)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Child month of birth fixed effect	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Constant	1.519	2.174	0.271	0.413	-0.149	0.090
	(1.669)	(1.941)	(0.646)	(0.670)	(1.001)	(1.022)
R-squared	0.360	0.379	0.235	0.224	0.225	0.216
Number of children	203	203	241	241	241	241

Robust standard errors clustered at the household cluster level are reported in parenthesis.

The dependent variables are *Antenatal care facility*, *Antenatal visits*, and *Antenatal care provider*. The *Antenatal care facility* variable is a dummy variable that takes the value of "1" if mothers received antenatal care from a government hospital, government health post, private hospital, or government health centers; otherwise, it takes the value of "0". The *Antenatal visits* variable represents the continuous count of antenatal visits made by a mother. The *Antenatal care provider* variable is a binary indicator, assigned "1" if the antenatal care provider was a doctor, nurse, midwife, auxiliary midwife, or community extension health worker, and "0" otherwise. The variables of interest are *Exposed cluster*, *Alive during conflict, and Farm household*. *Exposed cluster* is the *Treatment* variable that takes the value of “1” if cluster is within 10km radius of at least one conflict event from August 2017 to the time of household survey (Nigeria DHS 2018 survey was conducted from August 2018 to December 2018) and “0” if otherwise. *Alive during conflict* is the *Post* variable that takes the value of “1” if a child was alive during conflict and “0” if the child was born after conflict ended in their cluster. *Farm household* is a dummy variable that takes the value of “1” if a household’s head or their spouse are engaged in agriculture and “0” otherwise. Other independent variables used include child’s age in months, child’s gender, household head age, household head gender, household head years of education, household size and number of children in the household. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS and ACLED

Table A.5: Difference in Means of Household Characteristics Before and After Caliper Matching using conflict events from September 2013 to 2018

Variable	(1) Unexposed cluster	(2) Conflict-exposed cluster	(3) Difference
Matching variables			
No matching			
Non-Fulani households	0.911	0.969	0.037**
	(0.285)	(0.173)	(0.015)
Farm households	0.377	0.207	-0.140***
	(0.485)	(0.406)	(0.025)
Mother's education level	1.437	1.817	0.232***
	(0.985)	(0.937)	(0.051)
Household head years of education	5.126	4.711	-0.356***
	(1.379)	(1.548)	(0.098)
Rural households	0.412	0.284	0.000
	(0.492)	(0.452)	(0.000)
Number of children	*1328*	*766*	*2094*
Number of households	*1008*	*454*	*1462*
Number of clusters	*423*	*148*	*571*
Caliper matching			
Non-Fulani households	1.000	1.000	0.000
	(0.000)	(0.000)	(0.000)
Farm households	0.262	0.245	0.003
	(0.441)	(0.431)	(0.016)
Mother's education level	1.778	1.817	0.067
	(0.904)	(0.933)	(0.043)
Household head years of education	5.045	5.030	-0.126
	(1.433)	(1.387)	(0.089)
Rural households	0.276	0.245	0.000
	(0.448)	(0.431)	(0.000)
Number of children	*311*	*519*	*830*
Number of households	*225*	*306*	*531*
Number of clusters	*96*	*96*	*192*

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS(2018) and ACLED.

Difference in means of household characteristics by matching methods.

i. **No matching**

For this matching method, exposed clusters are not matched to unexposed clusters. We ran our main regression analysis using the no matching sample with cluster group fixed effect. The cluster group variable in the DHS dataset categorizes clusters based on their state, geographical region within the state, and rural or urban status. Hence, clusters that share these characteristics are grouped into the same cluster stratum. For instance, if clusters 1, 2, and 3 are located in the rural region of the northern area of Adamawa state, they would be grouped into the same cluster group. While this strategy allows the control of differences across cluster group, it may not control for cluster non-geographical characteristics such as the education level or occupation of residents living in the cluster, which could cause endogeneity bias.

Table A.6 shows the difference in means of household level variables that could affect cluster conflict exposure in conflict exposed cluster and unexposed cluster. A majority of the 1012 households in the no-matching sample live in unexposed clusters. Although there are no statistically significant differences in the average household head years of education and proportion of rural households between conflict-exposed clusters and unexposed clusters, the proportion of non-Fulani households and farm households in conflict-exposed clusters is lower than that of unexposed clusters.

Moreover, the average mother education level is lower in unexposed clusters compared to conflict exposed clusters. This implies that conflict-exposed clusters differ from unexposed clusters in characteristics that could affect both the outcome variables and clusters' conflict exposure. Hence, there is a need to implement other matching methods that facilitate the balance between conflict-exposed clusters and unexposed clusters with respect to variables that could cause endogeneity bias.

Table A.6: No matching scenario

Variable	(1) Control group	(2) Treatment group	(3) Difference
Non-Fulani households	0.963	0.952	0.025*
	(0.189)	(0.214)	(0.014)
Farm households	0.444	0.230	-0.124***
	(0.497)	(0.422)	(0.032)
Mother education level	1.577	1.922	0.313***
	(0.897)	(0.832)	(0.061)
Household head years of education	5.046	5.077	0.004
	(1.442)	(1.574)	(0.125)
Rural households	0.404	0.252	0.000
	(0.491)	(0.435)	(0.000)
Number of children	1020	394	1414
Number of households	782	230	1012
Number of clusters	326	76	402

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS(2018) and ACLED.

ii. **Near matching**

For this matching method, we matched conflict-exposed clusters to the nearest unexposed clusters using the geodetic distance between clusters' geo-coordinates. The motivation for this method is that matched clusters that are close in proximity are likely to share many similar traits. The near matching method is the only matching method in this study that matches control clusters to treated clusters with replacement. Thus implying, a control cluster may be matched to more than one treated cluster.

However, the flaw with this strategy is that it cannot control for all cluster characteristics, which could potentially cause endogeneity bias. For instance, a conflict-exposed urban cluster might be matched to an unexposed rural cluster because it is the closest in proximity to the conflict-exposed cluster. This is demonstrated in Table A.7 where the average proportion of farm households and average mother education level in conflict-exposed clusters and unexposed clusters differ significantly by 28% and 19% respectively. The near-matching method does not fare any better compared to the no matching strategy in terms of the number of balanced variables between conflict-exposed clusters and unexposed clusters. Although the sample size is considerably lower in the near-matching scenario compared to the no matching scenario, the number of conflict-exposed households remains unchanged.

Table A.7: Near matching scenario

Variable	(1) Control group	(2) Treatment group	(3) Difference
Non-Fulani households	0.944	0.970	0.023
	(0.230)	(0.172)	(0.018)
Farm households	0.550	0.217	-0.286***
	(0.498)	(0.413)	(0.036)
Mother education level	1.656	1.826	0.191***
	(0.829)	(0.918)	(0.065)
Household head years of education	4.801	4.901	-0.027
	(1.662)	(1.525)	(0.150)
Rural households	0.487	0.252	-0.167***
	(0.500)	(0.435)	(0.028)
Number of children	617	394	1,011
Number of households	210	230	440
Number of clusters	81	76	157

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS(2018) and ACLED.

iii. **P-score matching**

For this method, we ran a probit regression using the conflict exposure variable as the dependent variable and the matching variables as independent variables. Then we ran our main regression analysis by restricting the sample to observations that are within common support. This method facilitates the matching of clusters based on having a similar probability of exposure to Farmer-Herder conflict events given the matching variables**.** However, there are statistically significant differences in means of matching variables between conflict exposed and the matched unexposed clusters as reported in Table A.8. Further, we attempted to exact-match clusters by their cluster group and then conduct a p-score matching within each cluster group. However, this resulted in a very small sample within common support.

Table A.8: Propensity score matching scenario

Variable	(1) Control group	(2) Treatment group	(3) Difference
Non-Fulani households	0.975	0.974	0.028**
	(0.157)	(0.161)	(0.012)
Farm households	0.418	0.220	-0.115***
	(0.494)	(0.415)	(0.032)
Mother education level	1.628	1.833	0.104
	(0.899)	(0.906)	(0.065)
Household head years of education	5.050	4.789	-0.207*
	(1.400)	(1.616)	(0.119)
Rural households	0.398	0.251	-0.000
	(0.490)	(0.435)	(0.000)
Number of children	985	389	1,374
Number of households	756	227	983
Number of clusters	312	73	385

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS(2018) and ACLED.

iv. **Matching Algorithm**

For this method, all matching variables except the cluster group variable were converted into cluster-level variables by taking the mean of the variable for each cluster. For instance, the average household wealth index in a cluster is a cluster-level variable derived by taking the mean of household wealth index for all households in the cluster. The cluster-level variables are then converted into categorical variables. A cluster group variable was generated using the categorical cluster-level matching variables. Groups that contain at least one conflict exposed cluster and at least one unexposed cluster are kept, and group with either only conflict exposed cluster(s) or only unexposed cluster(s) are removed from the sample. The cluster group variable was used as a fixed effect in the main regression analysis. The difference in means in the matching variables between conflict-exposed clusters and unexposed clusters is reported in Table A.9. More than half of the 247 households in the matching algorithm sample are in unexposed clusters. All the matching variables are balanced between both conflict exposure groups except for the percentage of farm households and average mother education level in the cluster. Conflict exposed clusters have a larger proportion of farm households compared to unexposed clusters. While the matching algorithm scenario fares better than the no-matching scenario in terms of balance variables, the matching algorithm sample size is only a small fraction of the no-matching sample.

Table A.9: Matching algorithm scenario

Variable	(1) Control group	(2) Treatment group	(3) Difference
Non-Fulani households	1.000	1.000	0.000
	(0.000)	(0.000)	(0.000)
Farm households	0.298	0.328	0.167***
	(0.459)	(0.471)	(0.038)
Mother education level	1.802	1.802	-0.188**
	(0.836)	(0.826)	(0.078)
Household head years of education	5.061	4.688	-0.248
	(1.345)	(1.698)	(0.172)
Rural households	0.389	0.207	-0.000
	(0.489)	(0.407)	(0.000)
Number of children	171	205	376
Number of households	131	116	247
Number of clusters	51	36	87

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS(2018) and ACLED.

v. **Coarsened exact matching.**

Similar to the matching algorithm scenario, the cluster group variable and categorical versions of the cluster-level matching variables were used to implement this matching method. Following this, the categorical variables were subjected to an exact matching algorithm to identify the matched clusters and remove unmatched clusters. The CEM algorithm generates a set of cluster groups with uniform values for each categorical variable within each group. Clusters in groups that contain at least one conflict exposed cluster and unexposed cluster are kept while clusters in the remaining groups are removed from the sample. Table A.10 reveals that of the 351 households in the coarsened exact match sample, over 50% are in unexposed clusters. All matching variables are balanced between conflict-exposed clusters and unexposed clusters except the proportion of non-Fulani households, average mother education level and proportion farm households in the cluster.

Table A.10: Coarsened exact matching scenario

Variable	(1) Control group	(2) Treatment group	(3) Difference
Non-Fulani households	1.000	0.972	-0.024***
	(0.000)	(0.165)	(0.009)
Farm households	0.178	0.224	0.097***
	(0.383)	(0.418)	(0.024)
Mother education level	1.957	1.797	-0.212***
	(0.770)	(0.869)	(0.054)
Household head years of education	5.059	4.616	-0.198
	(1.361)	(1.625)	(0.141)
Rural households	0.269	0.259	-0.009
	(0.445)	(0.439)	(0.020)
Number of children	273	244	517
Number of households	208	143	351
Number of clusters	85	46	131

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS(2018) and ACLED.

vi. **Supported Score-based Neighborhood matching scenario**

For this matching strategy, a probit regression was conducted using cluster-level variables including the cluster group variable. Using the propensity score predicted from the probit regression, the ultimatch command in STATA was employed to conduct a neighborhood matching on the sample that is on common support while specifying an exact matching on cluster group. The supported score-based neighborhood matching method matched conflict-exposed clusters to unexposed clusters without replacement. Table A.11 presents the difference in means of matching variables between conflict-exposed clusters and unexposed clusters in the score-based neighborhood-matching sample. Over 60% of the 393 households in the neighborhood-matching sample are in conflict-exposed clusters. Further, there are statistically significant differences in the proportion of farm households, average household head years of education, and average household wealth index between conflict-exposed clusters and unexposed clusters.

Table A.11: Supported Score-based Neighborhood matching scenario

Variable	(1) Control group	(2) Treatment group	(3) Difference
Non-Fulani households	0.945	0.987	0.046***
	(0.229)	(0.115)	(0.017)
Farm households	0.299	0.200	-0.079**
	(0.460)	(0.401)	(0.032)
Mother education level	1.646	1.873	0.180**
	(0.988)	(0.805)	(0.080)
Household head years of education	5.056	4.992	-0.514***
	(1.400)	(1.651)	(0.161)
Rural households	0.331	0.260	0.000
	(0.472)	(0.440)	(0.000)
Number of children	161	260	421
Number of households	127	150	277
Number of clusters	52	47	99

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria DHS(2018) and ACLED.

Appendix B - Appendix for Chapter 2

Table B.1: Effect of Conflict on Crop Income within 10km Exposure Radius Using Balanced Panel

	Model 1	Model 2	Model 3	Model 4	Model 5
Conflict events (10km)	-85.524	-164.009	-150.771	-223.945	-214.858
	(94.180)	(299.532)	(300.820)	(263.582)	(264.267)
Land slope (percent)		11.946	4.445	-8.303	-13.537
		(44.690)	(43.754)	(44.112)	(43.460)
Age dependency ratio		-67.178	-67.410	**-82.490***	**-82.837***
		(50.207)	(50.277)	**(46.808)**	**(46.895)**
Household Size		12.846	3.790	18.200	9.825
		(37.468)	(37.438)	(34.577)	(34.543)
Female household head		**-311.225***	-310.334	**-339.546***	**-339.824***
		(188.147)	(189.445)	**(186.110)**	**(187.675)**
Household head's age		34.510	34.563	30.326	30.816
		(25.103)	(25.109)	(23.517)	(23.528)
Household head's age squared		-0.333	-0.337	-0.297	-0.304
		(0.217)	(0.217)	(0.206)	(0.206)
Household distance to administrative center (km)		-0.131	-0.804	-0.373	-1.409
		(2.883)	(3.012)	(3.482)	(3.382)
Household distance to market (km)		-17.518	17.797	-21.562	18.478
		(19.108)	(36.778)	(18.947)	(34.657)
Household distance to nearest major road (km)		**-6.615****	**-6.684****	**-7.190****	**-7.545*****
		(2.690)	**(2.765)**	**(2.822)**	**(2.825)**
Household distance to nearest border crossing (km)		0.542	0.525	-2.020	-2.510
		(2.520)	(2.763)	(2.918)	(2.826)
Land size in hectares		**88.343*****	**88.925*****	**57.928*****	**58.161*****
		(16.768)	**(16.786)**	**(15.809)**	**(15.834)**
Rural households		-902.043	-165.757	-529.749	205.890
		(745.723)	(529.285)	(685.589)	(446.835)
Annual mean temperature		-138.649	-364.551	-64.714	-278.749
		(346.785)	(265.166)	(352.742)	(249.931)
Average 12-month total rainfall(mm)		-1.074	-0.720	2.403	3.137
		(2.064)	(1.990)	(2.673)	(2.366)
Average EVI value at peak of greenness within growing season		-833.249	697.353	-6810.949	-2935.589
		(4771.131)	(4358.422)	(5741.772)	(4830.644)
Constant	1005.531***	7366.373	9182.173	5766.394	5588.317
	(26.533)	(10945.17)	(7720.153)	(11817.67)	(7987.740)
Household fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Survey wave fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
LGA fixed effects	*No*	*No*	*Yes*	*No*	*Yes*
State-specific time trend	*No*	*No*	*No*	*Yes*	*Yes*
R-squared within	0.043	0.07	0.076	0.205	0.212
R-squared overall	0.021	0.003	0.058	0.011	0.0009
Observations	6288	5167	5167	5167	5167

Standard errors robust to heteroskedasticity are reported in parenthesis. The dependent variable is *Crop income* which is the value of crop production less total explicit input expenditure. The variable of interest is Conflict events which measures the number of conflict events within 10km radius of each household. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Nigeria GHSP and ACLED.