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The Effect of Violent Conflict on the Socioeconomic Condition of Households in Nigeria: The Case of Kaduna State

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HiCN Working Paper 373

November 2022

Keywords: Violent conflict, Conflict exposure, Socioeconomic condition, Poverty, Kaduna State, Nigeria

JEL codes: D3, O12, R20

Abstract
The incidence and intensity of violent conflict in Nigeria have been rising steadily since 2016. However, the states across the country are not equally affected. Moreover, the nature of the conflicts and the conditions under which they occur vary across Nigeria's states. Relying on novel survey data that was collected from Kaduna, the second state most affected by violent conflict in Nigeria, this study examines the effect that exposure to violent conflict has on the socioeconomic condition of households. The instrumental variable regressions show that violent conflict worsens the socioeconomic condition of households. A unit increase in the number of violent conflicts within the 30km buffer around the dwellings of the households increases the likelihood of them being unable to meet their food needs by 0.3 percent. This finding is robust to alternative data, buffer sizes, and estimation techniques. Improvements in state capacity was found to reduce the likelihood of households being in a poor socioeconomic condition. This is because economic activity does not thrive in an environment characterized by insecurity.

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Financial support from the German Federal Ministry for Family Affairs, Senior Citizens, Women and Youth (BMFSFJ) is gratefully acknowledged.

1.0. Introduction

Data from the Armed Conflict Location and Events Database (ACLED) (Raleigh et al., 2010) shows that the incidence of violent conflict in Nigeria has been rising steadily since 2016. There were 2,579 incidents in 2021 alone, making it Nigeria's most violent year since 1997 (Violent conflicts are incidents that fall under the categories of Battles, Violence against civilians, and Explosions/Remote violence).[1] Besides contending with attacks perpetrated by the jihadist group *Boko Haram*, Nigeria also struggles with deadly clashes between nomadic herders and sedentary farmers. In 2018, farmer-herder clashes caused 1,158 fatalities, dwarfing the 589 fatalities attributed to *Boko Haram* (Institute for Economics and Peace, 2019). Kidnapping and banditry, especially in the country's North-West geopolitical zone, is also on the rise (Osasona, 2021; Akinwotu, & Uangbaoje, 2021), coupled with the fight for secession in the predominantly Igbo Eastern Region of the country that has persisted for over two decades and caused several casualties (Maiangwa, 2021). Nigeria had a rank of 37 out of 44 Sub-Saharan African countries in the 2022 Global Peace Index (GPI), making it the eighth least peaceful country in the region (Institute for Economic and Peace, 2022). Some commentators have blatantly referred to Nigeria as a failed state because of the government's inability to provide security for its citizenry (Rotberg & Campbell, 2021).

When the focus is shifted to the socioeconomic wellbeing of Nigeria's population, the results are also dismal: Data from the United Nation's Population Division shows that Nigeria had a life expectancy of 55 years in 2020, which is one of the lowest in the world, exceeding only Lesotho, Chad, and Central African Republic. According to the UN Inter-agency Group for Child Mortality Estimation, Nigeria's infant mortality rate declined from 84.3 to 72.2 between 2010 to 2020, but it still lagged behind the averages for Sub-Saharan Africa and the World, which were 50.3 and 27.4 respectively in 2020.[2] Poverty is also endemic, with a survey conducted in 2019 showing that 40.1 percent of Nigerians live below the poverty line of 137,430 naira (approximately US$ 361) per annum (Nigerian National Bureau of Statistics, 2020).

Statistics computed at the country level conceal the nuances within the country. The incidence of violent conflict and poverty vary across Nigeria's 36 states. While Nigeria's

[1] Tables 8 and 9 in the appendix show the distribution of violent conflict across Nigeria's states and the annual trend of violent conflict from 1997 to 2021 respectively.

[2] The data for life expectancy and infant mortality could be accessed at the World Bank's World Development Indicators (WDI) database: https://databank.worldbank.org/source/world-development-indicators

national poverty headcount rate was 40.1 percent in 2019, the estimate was over 85 percent in the states of Jigawa, Sokoto, and Taraba. In contrast, the poverty rate in the states of Lagos, Delta, and Osun was below 10 percent (Nigerian National Bureau of Statistics, 2020). A closer examination of the ACLED data shows that Borno State alone accounted for 24 percent of the 14,247 violent conflicts that occurred in Nigeria between 1997 to 2021. In contrast, 38 incidents were recorded in Kebbi State during this period.

Using novel survey data collected from Kaduna State in 2021, this study seeks to examine the effect of violent conflict on the socioeconomic condition of households in the state. More specifically, it seeks to answer the following question:

What is the effect of exposure to violent conflict on the socioeconomic condition of households?

Kaduna has the second highest incidence of violent conflict in Nigeria after Borno. 1,013 violent conflicts occurred there between 1997 to 2021, which is equivalent to 7 percent of the total incidents in Nigeria. These incidents have caused over 7,000 casualties. The incidence and intensity of violent conflict in the state have been rising steadily since 2017. Although it is generally agreed that violent conflict has worsened the socioeconomic condition of households in Nigeria, not many studies have examined this causal relationship. To the best of my knowledge, the study by Odozi and Oyelere (2019), which relies on the Nigeria General Household Survey data and ACLED data, is the only study that has done this. They measure exposure to conflict using the total number of fatalities in the state where the respondents reside. This is problematic because it is difficult to determine actual fatality numbers during conflict. "Fatality data are typically the most biased and least accurate component of any conflict data." (ACLED 2021, p. 32).

While country-level studies are insightful and provide a holistic view, they often gloss over the fact that the conditions under which conflicts occur as well as the kind of conflicts vary within the country. In Borno State for instance, majority of the conflicts that have occurred there involve the Islamist group *Boko Haram* and its affiliates. Most of the incidents that have occurred in Kaduna State are intercommunal in nature, involve culturally defined groups, and are characterized by reprisals. Two prominent conflicts in Kaduna are the clashes between Christians and Muslims, and the clashes between Fulani nomadic pastoralists and the sedentary population. The data collected from Kaduna enables me to zoom in on the state and take the local context within which the conflict occurs into account in the analysis. Moreover, the measure for conflict exposure that I have used in this study is based on the incidence of conflict rather than the number of fatalities. I only use the latter as a robustness check. Rather than measuring exposure to violent conflict using the Local Government Area (LGA) administrative boundaries in Kaduna, I rather measure it using buffers that I drew around the dwellings of the households using QGIS software. This allows for more variation in the conflict exposure variable and allows for a direct comparison between the households since the buffers are of equal sizes. Moreover, administrative boundaries in Nigeria, especially at the subnational level, are not clearly defined. The results of this study will be useful to policymakers who are interested in understanding how violent conflict affects the socioeconomic health of households in Nigeria. This could aid them in developing relevant interventions.

This paper proceeds as follows: Section 2 reviews the literature on the nexus between conflict and socioeconomic condition and states the hypothesis. Section 3 discusses the trend of violent conflict in Kaduna State. Section 4 operationalizes the variables that will be used to estimate the regression models, presents the summary statistics, discusses the sampling strategy, and specifies the general form of the model to be estimated. Section 5 discusses the regression results, while section 6 summarizes the paper and concludes.

2.0. Theoretical considerations

Conflict could affect the socioeconomic condition of households through different mechanisms. Conflict causes forced displacement and the destruction/depletion of household assets. This could force households, especially those that are already vulnerable, into poverty and food insecurity (Mercier et al., 2020; Verwimp & Van Bavel, 2013; Ibáñez & Moya, 2010). In situations where households rely on fixed assets like land for their income and sustenance, displacement due to conflict could deny them access to their lands, which in turn stifles their income-generating capacity (Mehler, 2005, p. 106). In the instances where the displaced households are fortunate to return to their previous dwellings after the conflict has ended, they may have to contend with lands contaminated with landmines. A report by the Mines Advisory Group shows that Nigeria is among the top five countries in the world with the highest casualty rate from landmines. Between January 2016 to August 2020, there were 697 accidents involving landmines which caused an estimated 1,052 casualties. These incidents are concentrated in the North-Eastern region of the country where *Boko Haram* activity is concentrated (Mines Advisory Group, 2020).

Even when the conflict does not lead to displacement, it could still cause the death or injury of one or more members of the household. This makes the household susceptible to poverty. This is especially so if the maimed or injured member was the breadwinner. With a fall in income, households may resort to financing consumption with their savings. When savings are depleted, there is less money available to channel towards investment, and this could push already vulnerable households into the poverty trap (Sachs, 2005, pp. 56-57). Conflict also alters the gender structure of households: the ratio of male to female household members decrease because more men tend to die from violent conflict (McDonald et al., 2012). This leads to changes in gender roles and intra-household relations as more women become household heads and engage in activities that were typically done by men in times of peace (Brück & Schindler, 2009, pp. 298-299). The survey data upon which this study relies shows that 52 of the 67 respondents whose spouse had died were female.

Conflict creates an atmosphere of fear and insecurity under which economic activities do not thrive (Collier & Duponchel, 2013; Deininger, 2003). Household members may be afraid to go to the farm or to travel to market to sell their agricultural surpluses because of fear that they might be attacked. This limits economic participation which in turn could shrink their income-generating capacity. This is especially relevant in the case of Kaduna where over 1.3 million households are engaged in crop cultivation. 91 percent of these households cultivate their crops solely for subsistence or for both subsistence and commercial purposes (Kaduna State Bureau of Statistics, 2016). Conflict worsens an already bad situation. This is because even in its absence, agricultural households already contend with the adverse effects of climate change like droughts and rising temperature that reduce crop yield (Hassan et al., 2019; Thompson et al., 2010).

Another mechanism through which conflict affects the socioeconomic condition of households is health. Hoeffler and Reynal-Querol (2003) show that post-conflict mortality rates tend to remain at par with that during conflict because of the destruction of public health infrastructure and the displacement of populations. Displaced populations who flee conflict zones in search of safety often live in camps that are in poor conditions. This makes them vulnerable to deadly diseases like malaria which could have been easier to treat and prevent in the absence of conflict (Anderson et al., 2011; Montalvo & Reynal-Querol, 2007). Conflict also undermines the government's effort at controlling the spread of disease (Fürst et al., 2009). Of the 241 million cases of Malaria that occurred globally in 2020, Nigeria alone accounted for 27 percent of them (World Health Organization, 2021). Malaria could lead to poverty because it limits school attendance among children and curtails labor productivity and income through the loss of workdays. It also causes death, especially among infants, forcing parents to compensate for this by having more children (Sachs, 2005, pp. 196-200). Larger households might be worse off socioeconomically because resources need to be divided among more people (Datt & Jolliffe, 2005; Lanjouw & Ravallion, 1995).

In a study conducted in Burundi, Verwimp and Van Bavel (2013) found that exposure to conflict reduced the probability of completing primary school. Forced displacement was the main mechanism through which conflict adversely affected schooling. Besides the destruction of physical educational facilities, conflict creates an atmosphere of insecurity that makes parents reluctant to send their children to school. In Kaduna State for instance, getting an education has become a risky endeavor due to the high incidence of students being abducted for ransom while at school (Akinwotu & Uangbaoje, 2021; Sadiq & Yaba, 2021). This prompted the state governor to close over 5000 primary and secondary schools in 2021 (Sahara Reporters, 2021; Obiezu, 2021). Even Abuja, the seat of the Nigerian federal government, is not exempt from such threats (Orjinmo, 2022; Vanguard, 2022). Low educational attainment correlates positively with unemployment and low income; low income and unemployment in turn increase the risk of conflict by reducing the opportunity cost of joining a rebel group (Collier et al., 2009; Collier & Hoeffler, 2004).

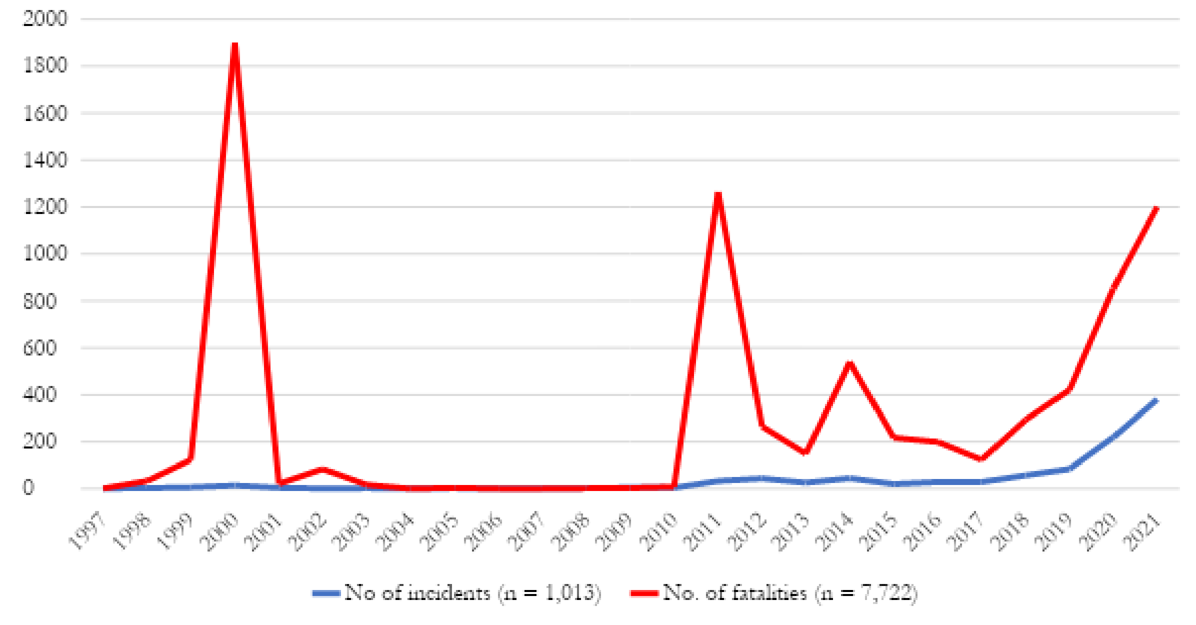
At the macro level, conflict leads to slow economic growth, capital flight, and increased military expenditure. An increase in military expenditure does not impel growth, but rather diverts funds that could have been used to provide infrastructure and social amenities that are growth-enhancing. Moreover, the arms purchased with the diverted funds are then used to destroy existing infrastructure during the conflict, resulting in a double loss (Collier et al., 2003, pp. 13-17). Even after the conflict ends, it may take several years for military expenditure to return to the pre-conflict level (Collier et al., 2003, pp. 20-21). The macro and micro effects of conflict are interwoven because macro problems are predicated upon micro fundamentals. The society is but an agglomeration of individuals, and disruptions at the individual level could cause disruptions at the societal level. Burton (1979, p. 64) alluded to this when he observed: “A social system is made up of units that are themselves entities. Each of these units enacts many roles in the complex society in which it is a member.”

It is acknowledged that poor socioeconomic condition increases the risk of violent conflict. However, this study is particularly concerned with the opposite relationship. The following hypothesis will be tested:

> H_a: *Exposure to violent conflict worsens the socioeconomic condition of households*

3.0. Trend of violent conflict in Kaduna State

Figure 1: Violent conflicts and fatalities in Kaduna State, 1997-2021 (ACLED)



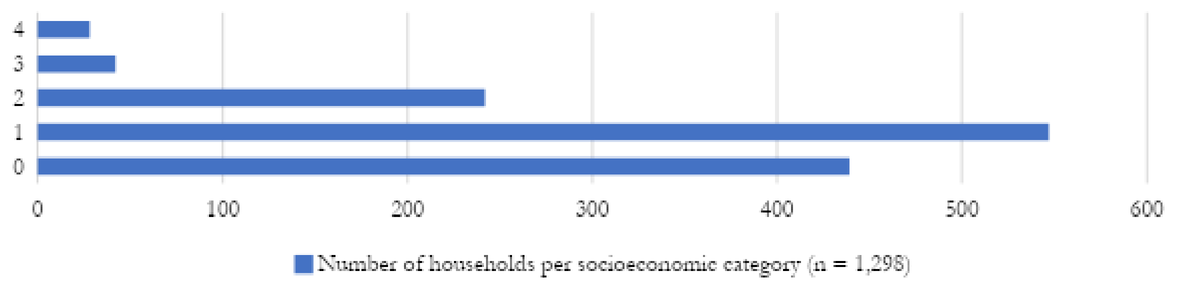
Data from ACLED (Raleigh et al., 2010) shows that there were 1,013 violent conflicts in Kaduna between 1997 to 2021, which were accompanied by 7,722 fatalities. 63 percent of the incidents were categorized as Violence against civilians, 28 percent as Battles, and 9 percent as Explosions/Remote violence. Figure 1 juxtaposes the incidence of violent conflict alongside the accompanying fatalities. The incidence and intensity of violent conflict has been rising steadily since 2017. 29 incidents were recorded in 2017. By 2021 the number had risen to 381, which is equivalent to a growth rate of 1,213 percent. The accompanying fatalities also rose from 123 to 1,201 during this period, corresponding to a growth rate of 876 percent. However, the number of fatalities appear to be more responsive to the intensity of the conflict than the incidence. The highest peak on the red fatality curve was in the year 2000, yet 14 incidents were recorded. Conversely, the 381 incidents that occurred in 2021 were accompanied by 1,201 fatalities. In terms of proportion, there were 136 fatalities per incident in 2000 compared to 3 fatalities per incident in 2021. The spike in the number of fatalities in 2000 was caused by the violent clashes that followed the introduction of Sharia law in the state by the then governor. Akin to Nigeria, Kaduna has a dyadic structure characterized by a predominantly Muslim northern region and a predominantly Christian southern region. The Muslim population supported the law while Christians opposed it vehemently, leading to violent clashes between both religious groups that left over 2000 people dead (Human Rights Watch, 2003). The second highest peak on the fatality curve was in 2011. This coincides with the post-election violence where Muslim supporters of the opposition candidate who lost the presidential elections systematically targeted and killed Christians and burnt churches. Christians retaliated by killing Muslims and burning mosques (Human Rights Watch, 2011). The most violent conflicts in Kaduna – in terms of fatalities – have been religiously motivated.

4.0. Data and methods

4.1. Operationalization of the variables

4.1.1. Dependent variable

Figure 2: Socioeconomic condition of households in Kaduna



The dependent variable measures the socioeconomic condition of households on a five-point ordinal scale. It was derived from the survey question, "Which of the following statements best describes the current economic situation of your household?" with the response options, "0 = Money is not enough for food (34%), 1 = Money is enough for food, but not for other basics like clothing, education, or sanitary products (42%), 2 = Money is enough for basic, but not enough for expensive durables like a motorbike/power generator (19%), 3 = We can afford to buy some expensive durables like a motorbike/power generator (3%), 4 = We can afford to buy almost anything (2%)." See figure 2 for a visualization. The survey had two sections: the household and individual sections. All members of the household were allowed to participate in answering the questions in the former section. This was necessary because the respondent who was randomly selected for the individual interview might not be the head of the household and thus not have much knowledge about its financial situation.

4.1.2. Explanatory variable

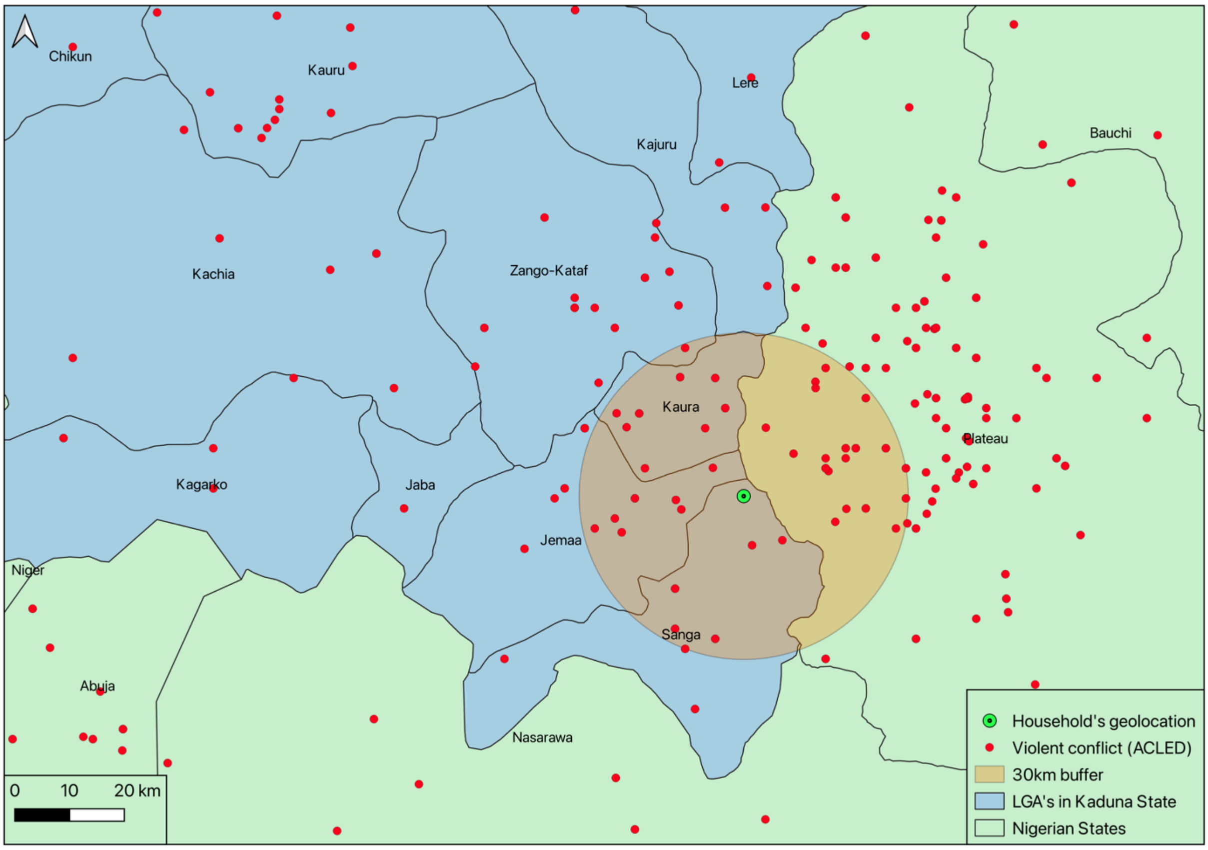


Figure 3: Measuring exposure to violent conflict

The explanatory variable, which is based on the ACLED data (Raleigh et al., 2010), measures the extent to which households are exposed to violent conflict.[3] Violent conflicts are incidents that fall under the categories of Battles, Violence against civilians, and Explosions/Remote violence. In this study, I focus on the cumulative effect of violent conflict. For this reason, I consider incidents that occurred from 1997 to 2020. The start date of 1997 was chosen because the ACLED data begins from that year. Although the ACLED data is updated in real time, all incidents that occurred post-2020 were excluded because the survey data from which the dependent variable is derived, was collected in 2021. This serves as a lag for the explanatory variable. The geolocations of the households were recorded during the survey. The ACLED dataset is also geocoded. Exploiting this information, I used QGIS software to draw buffers of various radii around the dwellings of the households and counted the total

[3] The ACLED dataset could be accessed here: https://acleddata.com/

number of violent conflicts within them. The higher the number of incidents within the buffer, the greater is the exposure to violent conflict and vice versa. Buffers are a more efficient way of measuring exposure to violent conflict than administrative boundaries. As shown in figure 3 where I use a single household for demonstrative purpose, the household's geolocation is in Sanga Local Government Area (LGA) in Kaduna State, yet conflicts that occur in the contiguous LGAs of Kaura and Jema'a, and the contiguous state of Plateau, are closer to the household's dwelling than some of the incidents in the particular LGA where the household is located. If I had used the LGA as the unit of analysis, I would have associated the households in each LGA with the total number of violent conflicts there, which is not very efficient. Moreover, administrative boundaries in Nigeria, especially at the LGA level, are not clearly defined. The use of buffers mitigates these challenges because they are unique for every household and are of equal sizes. This allows for a direct comparison between the households and also allows for more variation in the measure of conflict exposure. All the households had at least one violent conflict within the 30km buffer around their dwellings. Half of them had at least 40 incidents within the 30km buffer.

4.1.3. Control variables

Control variables for state capacity, economic development, precipitation, access to market, and land ownership will be added to the regression models. I considered two measures for state capacity: The first variable measures the distance from the dwellings of the households to the state governor's residence in kilometers and as-crow-flies, while the second variable measures the time it takes to reach a military base. The rationale behind the first variable is that the ability of the state government to exert control over its territory diminishes the farther one moves from the administrative center, and thus the risk of conflict increases (Le Billon, 2001). The latter measure for state capacity was derived from the question, "How far away from here is the closest military barracks (when driving by car)?", with the response options, "0 = Fewer than 20 minutes (22%), 1 = 20 minutes to 1 hour (40%), 2 = More than 1 hour (38%)." The expectation is that the nearer the dwellings of the households are to military bases, the better would be their socioeconomic condition. This is because their proximity to a military base might imply that the military would be more likely to intervene in the event of conflict outbreak, and this increases security. Economic activity does not thrive in an environment characterized by insecurity.

I used the mean nighttime light (Ghosh et al., 2021) within the buffer around the dwellings of the households and the total number of health facilities within the buffers as proxies for economic development. To measure access to markets, I computed the distance from the dwellings of the households to the nearest market in kilometers and as-crow-flies. Many households in Kaduna rely on the sale of their surplus agricultural output to generate income, thus their socioeconomic condition would depend on the extent to which they are able to access markets. Since many households in the state rely on rain-fed crop cultivation for their sustenance, I added a control variable for the average annual precipitation around the dwellings of the households for the year 2020. This data was obtained from Climatic Research Unit (CRU) at the University of East Anglia, UK (Harris et al., 2020). The last control variable is a dummy that takes a value of 1 if the household owns a plot of land 0 otherwise. It accounts for asset ownership.

4.1.4. Instrumental variable

I used the forest cover within the buffer around the dwellings of the households as an instrumental variable for exposure to violent conflict. More specifically, this variable measures the total forest pixels within the buffer as a proportion of the total land cover pixels. The steps taken to develop the instrumental variable and some of the control variables are explained in more detail in the appendix. I expect that forest cover will plausibly not directly influence the socioeconomic condition of the households, except through its effect on violent conflict. Some studies have shown that forests could provide strategic military advantages for rebels, thus increasing the risk of conflict (Schaub & Auer, 2022; Fearon & Laitin, 2003; Collier & Hoeffler, 2000). The forests in Kaduna have worsened the security challenges facing residents of the state. This is because they provide a safe haven for terrorists and bandits, making it difficult for security personnel to bring the perpetrators of violence to justice. The state's forests have also hampered the government's effort at rescuing innocent citizens who have been kidnapped for ransom because the abductors are familiar with the terrain within the forests and often use it to their advantage (Hassan-Wuyo, 2022; Gadzama et al., 2018). There are also reports of *Boko Haram* insurgents relocating from *Sambisa Forest* in Borno State to forests in Kaduna (Obiezu, 2022). This has prompted the state governor to call for the bombardment of the forests in the state to obliterate terrorists and bandits residing there (Sunday, 2022). The data for forest cover was obtained from the Copernicus Global Land Cover Service (Buchhorn et al., 2020).

4.2. Sampling strategy

As part of the Transnational Perspectives on Migration and Integration (TRANSMIT) research project, the WZB Berlin Social Science Center conducted a survey in Kaduna State in 2021.[4] 1,353 households were interviewed. Multi-stage clustered random sampling was used to select the households to be interviewed. Grid cells of 5 x 5km, which were called precincts, were developed using GIS software. These precincts were overlaid on a shapefile showing the administrative boundaries of Kaduna State, its senatorial districts, and LGAs.[5] Each precinct was comprised of smaller 0.5 x 0.5km grid cells. Four LGAs – Giwa, Birnin Gwari, Kauru, and Zangon Kataf – were excluded from the sampling frame because they were unsafe areas for enumerators to conduct interviews in due to the high risk of intercommunal conflict.

To ensure that this did not skew the sample, the population was first stratified according to the senatorial district. Samples were drawn within each of the senatorial districts in relation to their respective population shares. 109 precincts were randomly drawn with replacement, with probabilities corresponding to the population sizes within each of them. From each of the selected precincts, smaller 0.5 x 0.5km grid cells were randomly selected with probabilities corresponding to the size of the population within them. The smaller grid cells were drawn without replacement. Within each of the smaller grid cells, an average of 12 households were interviewed. The households were selected using a random walk approach, and the interviewee within the household was chosen using a simple random draw. It is difficult to obtain recent population estimates for Nigeria from official government sources because the last population census was conducted in 2006. Due to this constraint, the population for Kaduna was extrapolated from the 2020 gridded population estimates developed by Worldpop at the University of Southampton (Bondarenko et al., 2020).[6]

4.3. Descriptive statistics and analytical technique

Table 1: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Socioeconomic condition[φ]	1298	0.978	0.921	0	4
Violent conflict (30km)	1353	76.608	70.076	1	191

[4] For more information on the TRANSMIT project visit: https://www.dezim-institut.de/projekte/projekt-detail/transnational-perspectives-on-migration-and-integration-transmit-7-13/

[5] Each state in Nigeria comprises of 3 senatorial districts, and each senatorial district comprises of LGAs.

[6] The Worldpop gridded population data could be accessed at: https://www.worldpop.org/

Violent conflict (40km)	1353	121.701	92.668	4	316
Violent conflict (50km)	1353	167.285	116.306	7	492
Violent conflict (short) (30km)	1353	33.194	33.101	0	95
Violence against civilians (30km)	1353	44.047	37.562	1	139
Battles (30km)	1353	24.43	26.735	0	67
UCDP conflict (30km)	1353	27.914	25.701	0	105
Total fatalities (30km)	1353	839.044	859.745	4	2241
Mean fatalities (30km)	1353	9.188	5.538	0.5	37.25
Time to reach military base	1298	1.157	0.762	0	2
Distance to gov't house (km)	1353	82.31	58.333	0.841	191.407
Precipitation (mm)	1353	1055.555	37.606	976.167	1109.167
Distance to market (km)	1353	4.994	5.318	0.034	23.322
Health facilities (30km)	1353	248.379	98.141	63	429
Health facilities (40km)	1353	368.976	106.757	113	613
Health facilities (50km)	1353	508.352	143.088	218	834
Nighttime light (30km)	1353	1.406	1.696	0	4.035
Nighttime light (40km)	1353	0.919	0.977	0.006	2.296
Nighttime light (50km)	1353	0.675	0.666	0.006	2.61
Land ownership	1298	0.423	0.494	0	1
Forest cover (30km)	1353	0.202	0.039	0.12	0.258
Forest cover (40km)	1353	0.209	0.039	0.122	0.257
Forest cover (50km)	1353	0.212	0.04	0.125	0.26

Note: *φ is the dependent variable.*

The general form of the model to be estimated could be expressed thus:

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X'_{2t} + \varepsilon_t$$

Where Y_t is the dependent variable which measures the socioeconomic condition of the households. X_{1t} is the explanatory variable which measures the degree to which households are exposed to violent conflict. X'_{2t} is a vector of control variables measuring state capacity, economic development, access to markets, precipitation, and asset ownership. β_1 and β_2 are the coefficients of the explanatory and control variables respectively, while β_0 is the intercept. ε_t ε_t is the error term, and *t* the year in which the variables are measured.

The a priori expectation is that exposure to violent worsens the socioeconomic condition of households. However, the reverse is also plausible as poor socioeconomic condition could lead to violent conflict by reducing the opportunity cost of joining a rebel group (Collier & Hoeffler, 2004, 2000). This leads to the problem of reverse causation. To mitigate this problem, I considered only violent conflicts that occurred prior to 2021 while developing the explanatory variable. This lags the explanatory variable since the dependent variable is measured in 2021. Another potential problem is endogeneity: some independent variables that could influence the socioeconomic condition of the households may be excluded from the model, causing omitted variable bias. To attenuate this problem, I employed an instrumental variable approach. I treated the explanatory variable as endogenous and instrumented it with forest cover. My expectation is that forest cover would plausibly influence socioeconomic condition only through the mechanism of violent conflict. Since the dependent variable is ordinal with five categories, I estimated the model using the instrumental variable (IV) ordered probit model which relies on maximum likelihood estimation (MLE). Robustness checks were done using an alternative estimation method, data, and buffer sizes.

5.0. Results and discussions

Table 2 reports some regressions models showing the association between forest cover and exposure to violent conflict. The buffer size at which the relevant variables are measured is specified in parenthesis in the header along with the estimation technique. All the models were estimated using ordinary least squares (OLS) regression.

Table 2: Association between forest cover and violent conflict

Violent conflict$^{\#\varphi}$	**(1) (OLS) (30km)**	**(2) (OLS) (30km)**	**(3) (OLS) (40km)**	**(4) (OLS) (50km)**
Forest cover$^{\#}$	588.631***	375.32***	881.298***	2007.554***
	(46.81)	(23.722)	(39.822)	(48.253)
Time to reach military base		-3.876***	-3.217*	4.762**
		(1.028)	(1.782)	(2.347)
Distance to gov't house (km)		0.605***	1.058***	0.491***
		(0.034)	(0.062)	(0.065)
Precipitation (mm)		1.98***	4.81***	8.492***
		(0.224)	(0.387)	(0.508)
Distance to market (km)		-0.748***	-2.788***	-3.736***
		(0.137)	(0.219)	(0.301)

Health facilities#		0.079***	0.2***	0.366***
		(0.011)	(0.014)	(0.014)
Nighttime light#		47.344***	0.2***	101.177***
		(1.269)	(0.014)	(5.08)
Land ownership		-0.345	-2.598	-4.427
		(1.278)	(2.179)	(2.837)
Constant	-42.546***	-336.273***	-806.672***	-1434.114***
	(9.646)	(24.441)	(42.511)	(56.21)
Observations	1353	1298	1298	1298
R-squared	0.105	0.898	0.831	0.819

Note: *φ is the dependent variable, standard errors are in parenthesis, # denotes variables measured at the buffer level. *** p<0.01, ** p<0.05, * p<0.10.*

All the variables were also treated as continuous. An ordered model would be inappropriate because the dependent variable – violent conflict – has about 200 categories. Forest cover carried the expected positive sign and was significant at the 1 percent level, suggesting a direct association between forest cover and exposure to violent conflict. In model 2 where the control variables were added, the coefficient of forest cover decreased from 588 to 375, but it remained statistically significant at the 1 percent level and retained its positive sign. To check for the robustness of this finding, I estimated some models where I measured the relevant variables at the 40km and 50km buffer levels. As shown in models 3 and 4, forest cover retained its positive sign and was significant at the 1 percent level in both cases.

Table 3: Effect of violent conflict on socioeconomic condition I

Socioeconomic condition$^{\varphi}$	**(1) IV Probit (30km)**	**(2) IV Probit (30km)**	**(3) 2SLS (30km)**	**(4) IV Probit (40km)**	**(5) IV Probit (50km)**	**(6) IV Probit (30km)**
Violent conflict#	-0.005***	-0.011***	-0.011***	-0.005***	-0.003***	
	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	
Violent conflict (short)#						-0.025***
						(0.004)
Time to reach military base		-0.13***	-0.136***	-0.135***	-0.13**	-0.121***
		(0.048)	(0.044)	(0.05)	(0.051)	(0.046)
Distance to gov't house (km)		0.005***	0.008***	0.004**	0.002	0.004**
		(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
Precipitation (mm)		0.034***	0.042***	0.037***	0.037***	0.028***
		(0.011)	(0.011)	(0.012)	(0.012)	(0.01)

Distance to market (km)		-0.008	-0.013**	-0.013**	-0.011	-0.005
		(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
Health facilities#		-0.001	0.00	-0.001*	-0.00	-0.001*
		(0.001)	(0.00)	(0.00)	(0.00)	(0.00)
Nighttime light#		0.338***	0.582***	0.333***	0.211*	0.335***
		(0.085)	(0.16)	(0.128)	(0.126)	(0.082)
Land ownership		0.397***	0.346***	0.401***	0.406***	0.396***
		(0.061)	(0.051)	(0.061)	(0.062)	(0.061)
Intercept 1	-0.808***	3.129**		3.125**	3.042**	2.317**
	(0.086)	(1.229)		(1.328)	(1.441)	(1.143)
Intercept 2	0.247**	4.235***		4.259***	4.198***	3.392***
	(0.116)	(1.243)		(1.334)	(1.447)	(1.158)
Intercept 3	1.093***	5.123***		5.17***	5.127***	4.257***
	(0.147)	(1.257)		(1.341)	(1.454)	(1.174)
Intercept 4	1.482***	5.531***		5.589***	5.554***	4.656***
	(0.167)	(1.265)		(1.345)	(1.458)	(1.184)
Constant			-4.069***			
			(1.271)			
Observations	1298	1298	1298	1298	1298	1298
R-Squared			0.047			
Log pseudolikelihood	-8880.84	-8841.86		-9101.743	-9295.58	-7881.65

Note: *φ is the dependent variable, standard errors are in parenthesis, # denotes variables measured at the buffer level. *** p<0.01, ** p<0.05, * p<0.10.*

Table 3 presents the second-stage regression results for models examining the effect of exposure to violent conflict on the socioeconomic condition of households. All the models, except for model 3, were estimated using the IV probit regression. Model 1 shows the baseline results where no control variables were added. Violent conflict carried the expected negative sign and was significant at the 1 percent level, suggesting that increased exposure to violent conflict reduces the likelihood of households being in a good socioeconomic condition. The correlation between the error terms of the first and second stage regressions was 0.36, and it was significant at the 1 percent level indicating that there is indeed endogeneity and the use of an instrumental variable approach was appropriate.

In model 2 where all the control variables were added, Violent conflict remained significant at the 1 percent level and retained its negative sign. Keeping all covariates at their mean levels, the analysis showed that a unit increase in the number of violent conflicts within the 30km buffer around the dwellings of the households increases the likelihood of them being unable to meet their food needs by 0.3 percent.[7] As expected, Time to reach military base carried a negative sign. This is congruent with the a priori expectation that households residing close to a military base were likely to be in a good socioeconomic condition because of increased security which enables economic activities to flourish. This in turn led to improvements in the socioeconomic condition of the households. The distance to the State Governor's residence was significant at the 1 percent level and carried a positive sign that contravened the a priori expectation. This shows that the farther away households were from the administrative center, the better was their socioeconomic condition. A plausible explanation for this finding could be that the variable measures some other attribute than state capacity, for example urbanization. The seat of the government is often located in urban centers with a high population density. This in turn might be associated with a higher cost of living, which makes it more difficult for households to meet their basic needs. Moreover, the lower population density in the rural areas implies that more land is available for households to cultivate crops to meet their food needs, unlike urban centers which are characterized by land pressure due to the high population and less arable land. Precipitation carried the expected positive sign and was significant at the 1 percent level, indicating a direct relationship between rainfall and socioeconomic condition. Nighttime light was significant at the 1 percent level and carried the expected positive sign, showing a direct relationship between economic development and the socioeconomic condition of the households. The number of health facilities within the buffer was not significant. Land ownership carried a positive sign and was significant at the 1 percent level, indicating that households that owned assets were more likely to be in a good socioeconomic condition compared to those that did not.

As a robustness check, I treated all the variables as continuous and re-estimated the model using two-stage least squares regression (2SLS). The results, as shown in model 3, were consistent with those from the IV probit model. I also undertook a test for endogeneity. The Durbin and Wu-Hausman statistics were 5.26 and 5.24 respectively, both of which were significant at the 5 percent level. This shows that endogeneity indeed exists and provides further justification for estimating the models using an instrumental variable approach. As a further robustness check, I estimated models 4 and 5 with the relevant variables measured at the 40km and 50km buffer levels respectively. Violent conflict carried the expected negative

[7] The marginal effects for model 2 are reported in Table 5 in the appendix.

sign and was significant at the 1 percent level in both cases. Although this study focuses particularly on the cumulative effect of violent conflict, which explains why I considered the incidents within the buffers from 1997 to 2020, I still developed a variable to examine the effect of short-term conflict exposure on the socioeconomic condition of the households. To measure short-term conflict exposure, I computed the total number of violent conflicts that occurred within the 30km buffers only from 2018 to 2020. As shown in table 6, exposure to short-term violent conflict carried the expected negative sign and was significant at the 1 percent level. Keeping all covariates at their mean levels, the analysis showed that a unit increase in the number of short-term violent conflicts within the 30km buffer around the dwellings of the households increases the likelihood of them being unable to meet their food needs by 0.7 percent. This effect is over twice the size of the effect that long-term conflict exposure has on the socioeconomic condition of the households.[8]

Table 4 presents the regression results for some more robustness checks that I undertook. 91 percent of the violent conflicts that occurred in Kaduna from 1997 to 2021 fell under the categories of Violence against civilians (63 %) and Battles (28%). To determine the effect that the different kinds of violent conflict have on the socioeconomic condition of the households, I disaggregated the explanatory variable and estimated some models using its two main subcomponents.

Table 4: Effect of violent conflict on socioeconomic condition II

Socioeconomic condition[φ]	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	IV Probit	**IV Probit**	**IV Probit**	**IV Probit**	**IV Probit**
	(30km)	**(30km)**	**(30km)**	**(30km)**	**(30km)**
Violence against civilians[#]	-0.014***				
	(0.002)				
Battles[#]		-0.045***			
		(0.006)			
Total fatalities[#]			-0.001***		
			(0.00)		
Mean fatalities[#]				-0.091***	
				(0.016)	
UCDP conflict[#]					-0.019***
					(0.003)
Time to reach military base	-0.138***	-0.104**	-0.118**	-0.1**	-0.13***

[8] The marginal effects for model 6 are reported in Table 6 in the appendix.

	(0.049)	(0.043)	(0.047)	(0.044)	(0.049)
Distance to gov't house (km)	0.005***	0.004***	0.003**	0.002	0.005***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Precipitation (mm)	0.035***	0.029***	0.026**	0.022**	0.038***
	(0.011)	(0.01)	(0.01)	(0.01)	(0.011)
Distance to market (km)	-0.007	-0.008	-0.007	-0.004	-0.008
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
Health facilities#	-0.001	-0.001	-0.001	-0.001**	-0.001
	(0.001)	(0.00)	(0.001)	(0.000)	(0.001)
Nighttime light#	0.236***	0.483***	0.255***	0.074	0.215***
	(0.07)	(0.139)	(0.082)	(0.052)	(0.069)
Land ownership	0.409***	0.355***	0.396***	0.368***	0.403***
	(0.061)	(0.068)	(0.061)	(0.057)	(0.061)
Intercept 1	3.261***	2.447**	2.147*	1.161	3.619***
	(1.243)	(1.172)	(1.152)	(1.059)	(1.287)
Intercept 2	4.4***	3.424***	3.238***	2.177**	4.752***
	(1.248)	(1.235)	(1.162)	(1.067)	(1.293)
Intercept 3	5.316***	4.211***	4.117***	2.996***	5.663***
	(1.253)	(1.293)	(1.172)	(1.076)	(1.298)
Intercept 4	5.736***	4.573***	4.522***	3.373***	6.08***
	(1.257)	(1.323)	(1.179)	(1.082)	(1.302)
Observations	1298	1298	1298	1298	1298
Log pseudolikelihood	-7961.74	-7636.44	-12092.014	-5547.782	-7456.829

Note: *φ is the dependent variable, standard errors are in parenthesis, # denotes variables measured at the buffer level. *** p<0.01, ** p<0.05, * p<0.10. The first stage regressions have not been reported.*

As shown in models 1 and 2, Violence against civilians and Battles both carried negative signs and were significant at the 1 percent level, suggesting that they both increase the likelihood of households being in a poor socioeconomic condition. Although the first stage regressions have not been reported, forest cover was statistically significant at the 1 percent level and carried a positive sign in both instances. Even though fatality numbers during conflict are difficult to estimate, which makes them susceptible to bias, I still estimated some models with these. The fatality estimates measure the intensity of the conflict rather than its incidence. I developed this variable by computing the total number of fatalities within the buffers around the dwellings of the households. As shown in model 3, Total fatalities carried the expected negative sign and was significant at the 1 percent level, indicating that the intensity of conflict also affects the socioeconomic condition of households negatively.

Keeping all covariates at their mean levels, the analysis showed that an additional fatality within the 30km buffer around the dwellings of the households increases the likelihood of them being unable to meet their food needs by 0.02 percent.[9] Suffice to add that forest cover was significant at the 1 percent level and carried a positive sign in the first-stage regression which have not been reported. As an alternative measure for the intensity of the conflict, I computed the mean number of fatalities per incident within the 30km buffers around the dwellings of the households. As shown in model 4, Mean fatalities carried the expected negative sign and was significant at the 1 percent level.

As a final robustness check, I developed an alternative measure for Violent conflict using data obtained from the Uppsala Conflict Data Program's (UCDP) Georeferenced Event Dataset (GED) (Sundberg and Melander, 2013).[10] This variable measures the total number of conflict incidents within the 30km buffer around the dwellings of the households from 1989 to 2020. The start year of 1989 was used because the UCDP-GED dataset is available beginning from that year. The UCDP dataset differs from the ACLED dataset because it records only incidents that result in at least one fatality. The ACLED dataset is devoid of this criterion. As shown in model 5, UCDP conflict was significant at the 1 percent level and carried the expected negative sign which is congruent with the results from the earlier models.

6.0. Conclusion

Using an instrumental variable approach, this study examined the effect that exposure to violent conflict has on the socioeconomic condition of households in Kaduna, the state with the second incidence of violent conflict in Nigeria. Exposure to violent conflict was found to increase the likelihood of households being in a poor socioeconomic condition. Keeping all covariates at their mean levels, the analysis showed that an additional violent conflict within the 30km buffer around the dwellings of the households increases the likelihood of them being unable to meet their food needs by 0.3 percent. These results are robust to alternative estimation methods, data, and buffer sizes. The intensity of violent conflict, which was measured using the total number of fatalities within the buffers around the dwellings of the households, was also found to increase the likelihood of the households being in a poor socioeconomic condition.

[9] The marginal effects for model 3 are reported in Table 7 in the appendix.
[10] To access the UCDP dataset visit: https://ucdp.uu.se/downloads/

A direct relationship was found between precipitation and the socioeconomic condition of the households. This is not surprising given that over 1.3 million households in the state engage in rain-fed crop cultivation, most of who rely on the sale of their surplus output to generate income. State capacity, measured by the time it takes to reach the nearest military base from the dwellings of the households, carried a negative sign, suggesting that households residing close to a military base were more likely to be in a good socioeconomic condition. This is because the military are more likely to intervene in the event of an outbreak of conflict. This creates an atmosphere of security which is essential for economic activities to thrive, which in turn leads to improvements in the socioeconomic condition of the households. This implies that improvements in state capacity would be an effective strategy for improving the socioeconomic condition of households in the state.

Although this study focused particularly on the effect that exposure to violent conflict has on the socioeconomic condition of households, poor socioeconomic condition could also increase the risk of violent conflict. This bi-directional causal relationship leads to a reinforcement mechanism where each factor creates the conditions necessary for the other to occur. While the government needs to take concrete steps towards improving state capacity and reducing structural violence, this needs to be pursued alongside policies that are geared towards poverty reduction. The poverty headcount rate in Kaduna is 3.5 percentage points higher than the national average of 40 percent, indicating that poverty remains a serious problem in the state (Nigerian National Bureau of Statistics, 2020).

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Appendix

Table 5: Marginal effects at the mean for model 2 in Table 3

Socioeconomic condition$^{\varphi}$ **(Money)**	**Not enough for food**	**Enough for food, not basics**	**Enough for basics, not durables**	**Can afford expensive durables**	**Can afford almost anything**
	(0)	**(1)**	**(2)**	**(3)**	**(4)**
Violent conflict$^{\#}$	0.003***	0.001	-0.002***	-0.001***	-0.001**
	(0.00)	(0.001)	(0.00)	(0.001)	(0.001)
Time to reach military base	0.037**	0.016	-0.027***	-0.012**	-0.014*
	(0.015)	(0.011)	(0.01)	(0.005)	(0.007)
Distance to gov't house (km)	-0.001***	-0.001	0.001***	0.00**	0.001*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Precipitation (mm)	-0.01***	-0.004	0.007***	0.003***	0.004**
	(0.004)	(0.003)	(0.002)	(0.001)	(0.002)
Distance to market (km)	0.002	0.001	-0.002	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Health facilities#	0.00	0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nighttime light#	-0.097***	-0.041	0.07***	0.031***	0.036**
	(0.028)	(0.028)	(0.019)	(0.01)	(0.016)
Land ownership	-0.114***	-0.048	0.082***	0.037***	0.042***
	(0.025)	(0.03)	(0.016)	(0.009)	(0.016)

Note: *φ is the dependent variable, # denotes variables measured at the buffer level, *** p<0.01, ** p<0.05, * p<0.10. Numbers in parenthesis below the response categories are the numerical values assigned to them.*

Table 6: Marginal effects at the mean for model 6 in Table 3

Socioeconomic condition^φ (Money)	**Not enough for food**	**Enough for food, not basics**	**Enough for basics, not durables**	**Can afford expensive durables**	**Can afford almost anything**
	(0)	**(1)**	**(2)**	**(3)**	**(4)**
Violent conflict (short)#	0.007***	0.004	-0.005***	-0.003***	-0.003*
	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)
Time to reach military base	0.032**	0.02	0.024**	-0.012**	-0.016*
	(0.014)	(0.013)	(0.01)	(0.005)	(0.009)
Distance to gov't house (km)	-0.001**	-0.001	0.001**	0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Precipitation (mm)	-0.008**	-0.005	0.006**	0.003**	0.004*
	(0.003)	(0.003)	(0.002)	(0.001)	(0.002)
Distance to market (km)	0.001	0.001	-0.001	-0.00	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Health facilities#	0.00**	0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nighttime light#	-0.089***	-0.054*	0.066***	0.034***	0.043**
	(0.027)	(0.031)	(0.02)	(0.011)	(0.02)
Land ownership	-0.105***	-0.064**	0.078***	0.04***	0.051**
	(0.027)	(0.032)	(0.02)	(0.01)	(0.02)

Note: *φ is the dependent variable, # denotes variables measured at the buffer level, *** p<0.01, ** p<0.05, * p<0.10. Numbers in parenthesis below the response categories are the numerical values assigned to them.*

Table 7: Marginal effects at the mean for model 3 in Table 4

Socioeconomic condition$^{\varphi}$ **(Money)**	**Not enough for food**	**Enough for food, not basics**	**Enough for basics, not durables**	**Can afford expensive durables**	**Can afford almost anything**
	(0)	**(1)**	**(2)**	**(3)**	**(4)**
Total fatalities[#]	0.00***	0.00	-0.00***	-0.00***	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time to reach military base	0.033**	0.016	-0.024**	-0.011**	-0.014*
	(0.014)	(0.011)	(0.01)	(0.005)	(0.008)
Distance to gov't house (km)	-0.001**	-0.00	0.001**	0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Precipitation (mm)	-0.007**	-0.004	0.005**	0.003**	0.003*
	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)
Distance to market (km)	0.002	0.001	-0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Health facilities[#]	0.00*	0.00	-0.00*	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nighttime light[#]	-0.071***	-0.035	0.051***	0.025***	0.03**
	(0.025)	(0.022)	(0.018)	(0.009)	(0.015)
Land ownership	-0.109***	-0.055*	0.08***	0.038***	0.046***
	(0.25)	(0.03)	(0.017)	(0.009)	(0.017)

Note: *φ is the dependent variable, # denotes variables measured at the buffer level, *** p<0.01, ** p<0.05, * p<0.10. Numbers in parenthesis below the response categories are the numerical values assigned to them.*

Table 8: Distribution of violent conflicts across Nigeria's states (1997-2021)

State	**Frequency**	**Percent**	**Cumulative**
Abia	128	0.90	0.90
Adamawa	443	3.11	4.01
Akwa Ibom	143	1.00	5.01
Anambra	238	1.67	6.68
Bauchi	138	0.97	7.65
Bayelsa	414	2.91	10.56
Benue	630	4.42	14.98
Borno	3397	23.84	38.82
Cross River	211	1.48	40.30
Delta	640	4.49	44.80
Ebonyi	143	1.00	45.80

Edo	245	1.72	47.52
Ekiti	101	0.71	48.23
Enugu	156	1.09	49.32
Federal Capital Territory	212	1.49	50.81
Gombe	89	0.62	51.44
Imo	192	1.35	52.78
Jigawa	63	0.44	53.23
Kaduna	1013	7.11	60.34
Kano	206	1.45	61.78
Katsina	449	3.15	64.93
Kebbi	38	0.27	65.20
Kogi	228	1.60	66.80
Kwara	102	0.72	67.52
Lagos	461	3.24	70.75
Nassarawa	271	1.90	72.65
Niger	352	2.47	75.12
Ogun	193	1.35	76.48
Ondo	193	1.35	77.83
Osun	176	1.24	79.07
Oyo	188	1.32	80.39
Plateau	707	4.96	85.35
Rivers	569	3.99	89.35
Sokoto	180	1.26	90.61
Taraba	390	2.74	93.35
Yobe	390	2.74	96.08
Zamfara	558	3.92	100.00
Total	**14,247**	**100.00**	

Note: *Based on ACLED data (Raleigh et al. 2010).*

Table 9: Annual distribution of violent conflicts across Nigeria (1997-2021)

Year	Frequency	Percent	Cumulative
1997	108	0.76	0.76
1998	96	0.67	1.43
1999	142	1.00	2.43

2000	127	0.89	3.32
2001	96	0.67	3.99
2002	128	0.90	4.89
2003	175	1.23	6.12
2004	194	1.36	7.48
2005	98	0.69	8.17
2006	99	0.69	8.87
2007	178	1.25	10.11
2008	172	1.21	11.32
2009	156	1.09	12.42
2010	312	2.19	14.61
2011	266	1.87	16.47
2012	669	4.70	21.17
2013	704	4.94	26.11
2014	870	6.11	32.22
2015	834	5.85	38.07
2016	697	4.89	42.96
2017	864	6.06	49.03
2018	1278	8.97	58.00
2019	1293	9.08	67.07
2020	2112	14.82	81.90
2021	2579	18.10	100.00
Total	**14,247**	**100.00**	

Note: *Based on ACLED data (Raleigh et al. 2010).*

Additional data notes

Forest cover: This measures the total forest pixels as a proportion of the total land cover pixels within the buffers around the dwellings of the households. It was obtained from the Copernicus Global Land Cover Service which maps land cover characteristics across the globe. Land cover is classified into the following categories: forests, shrubland, herbaceous vegetation, herbaceous wetland, moss and lichen, bare/sparse vegetation, cropland, built-up areas, snow and ice, and permanent water bodies. The raw data is gridded, so I used QGIS software to compute the relevant statistics. This land cover data is available from 2015 to 2019. I used the 2019 data to develop the instrumental variable for this study. As a rule, all data analyzed using QGIS were first re-projected to the coordinate reference system (CRS) EPSG: 26392 Minna/Nigeria Middle Belt, before the relevant statistics were computed. This land cover dataset could be accessed at: https://land.copernicus.eu/global/products/lc

Nighttime light: This measures the mean annual nighttime light within the buffers around the dwellings of the households. The raw data is also gridded, so I used QGIS software to compute the relevant statistics. The mean nighttime light is derived by dividing the sum of pixels within the buffer by the number of pixels. The pixels are on a band ranging from 0 to 63. Assuming a buffer comprises of six pixels, four with a band of 50 and two with a band of 25, the mean pixel within the buffer will be derived thus: $\frac{4(50)+2(25)}{4+2} = 41.67$ $\frac{4(50)+2(25)}{4+2} = 41.67$. The estimates used in this study are for 2020, a year prior to the survey. This data could be accessed at: Earth Observation Group's database. https://eogdata.mines.edu/products/dmsp/

Precipitation: This measures the average annual precipitation around the dwellings of the households in 2020. This dataset is available in 0.5 x 0.5-degree grids cells. Each grid cell has a unique precipitation value. I estimated the precipitation values at the centroids for all the grid cells within Nigeria's administrative boundary, as shown in the first panel of figure 4.

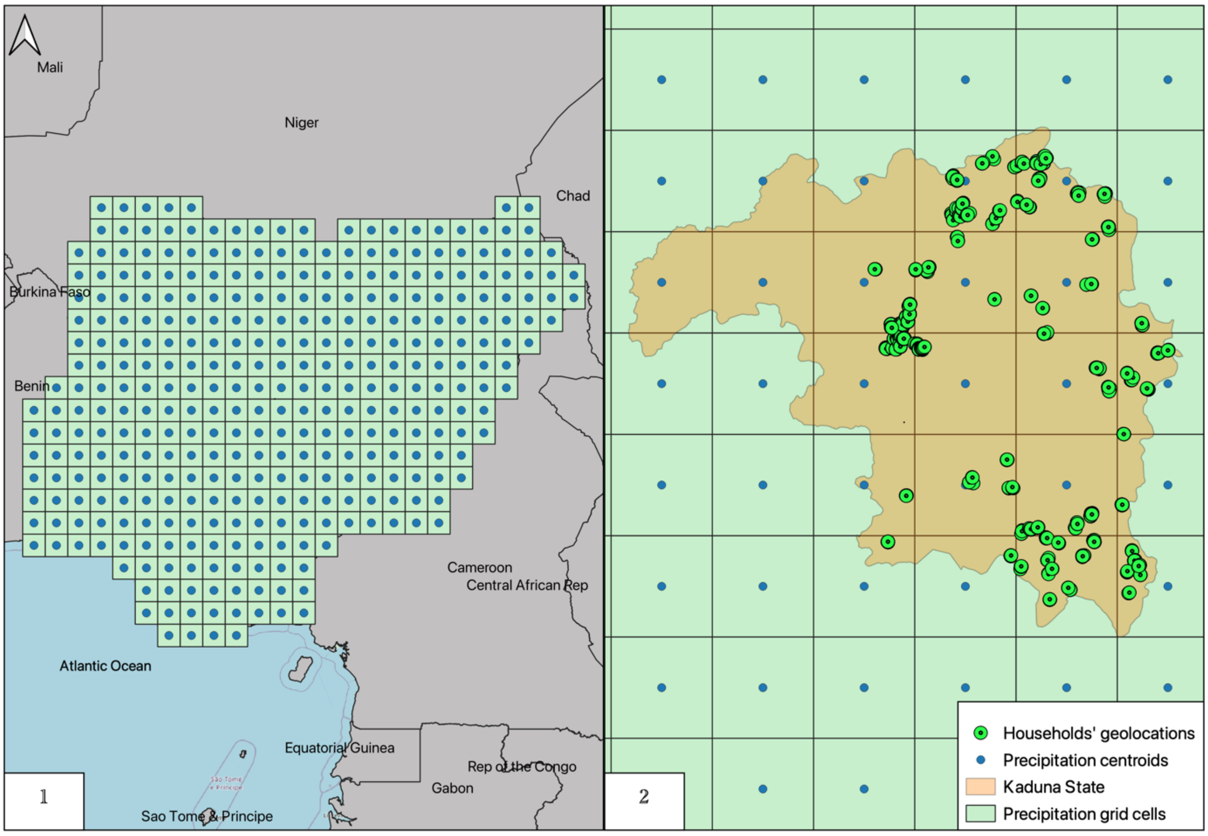

Figure 4: Determining the precipitation around the Households' geolocations

Subsequently, I matched the geolocations of the households with the precipitation values of the nearest centroid, as shown in panel 2. Since the centroids are equidistant from each other, it goes that the geolocations of the households will fall within the grid cell of the nearest centroid. The raw precipitation data is in netcdf format. I extracted the precipitation values at the centroids using R Studio. The matching was done using QGIS software. This raw data was obtained from the Climatic Research Unit (CRU) at the University of East Anglia, UK. Version 4.06 was used. It could be accessed at: https://crudata.uea.ac.uk/cru/data/hrg/

Distance to State Governor's house: This measures the distance from the dwellings of the households to the residence of the state governor in kilometers and as-crow-flies. See figure 5 for a visualization. The distances were calculated using QGIS software. The geolocations of the households in the diagram are arbitrary and are used only for a demonstrative purpose.

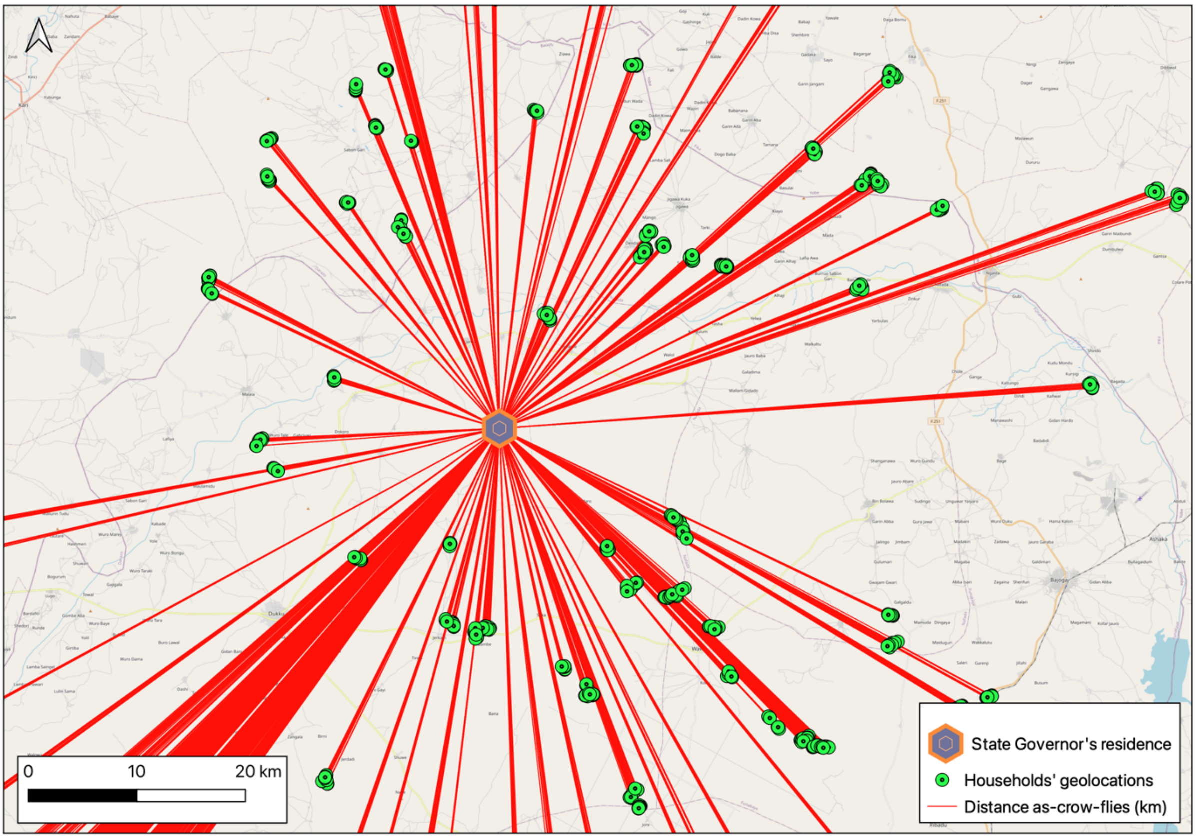

Figure 5: Measuring distance to State Governor's house

Distance to market: This measures the distance from the dwellings of the households to the nearest market in kilometers and as-crow-flies. The distances were calculated using QGIS software. The data with the geolocations of all the markets in Nigeria was obtained from the Georeferenced Infrastructure and Demographic Data for Development (GRID[3]) database. The metadata defines a market as a "regular gathering of people for the purchase and sale of provisions and other commodities; an area or arena in which commercial dealings are conducted." This data was collected between November 2017 and December 2018. It could be accessed at: https://grid3.gov.ng/

Health facilities: This measures the total number of health care facilities within the buffers around the dwellings of the households. This data was also obtained from the Georeferenced Infrastructure and Demographic Data for Development (GRID[3]) database. The metadata defines a healthcare facility as "primary, secondary, and tertiary entities that provide medical and/or healthcare services and/or engage in the use generally of natural and/or artificial materials to create or dispense drugs." This data was collected between November 2017 and December 2018.