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Violent conflict and hostility towards ethno-religious outgroups in Nigeria

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Abstract

This study examined the effect of exposure to violent conflict on hostility towards ethnic and religious outgroups among Nigeria's population and among its two major religious groups (Christians and Muslims). Violent conflict had a robust positive effect on outgroup hostility among the Nigerian population and among Christians. A plausible mechanism behind this finding is that the threat posed by violent conflict strengthens ingroup cohesion, erodes trust in outgroup members, and makes intergroup boundaries salient. This is especially so when the opposite party to the conflict constitutes a distinct cultural outgroup. The main conflict affecting Christians involves nomadic pastoralists of Fulani ethnicity, who are Muslims. Although both Christians and Muslims associate Muslims with extremism, Christians are more likely to do so. Among Muslims, violent conflict rather had a weak positive effect on outgroup hostility that was not robust to alternative model specifications. The null effect might be because the main conflict affecting Muslims – the Boko Haram insurgency – does not involve Christians. A significant number of Muslims are also affected by conflicts involving nomadic Fulani pastoralists.

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1.0. Introduction

A cursory look at Nigeria reveals that it has a dyadic structure comprising of a predominantly Christian Southern Region and a predominantly Muslim Northern Region. Although there are some overlaps between the two regions, the contrast between them is quite stark. The overlap between religion and ethnicity makes the fault line between the two regions even more salient.[1] This North-South bifurcation is apparent when one looks at Nigeria through the lens of the nine civilizations into which Samuel Huntington divided the world: Nigeria's Northern Region was associated with Islamic civilization, while the Southern Region was associated with African civilization (Huntington 1996).

This cultural divide has historical roots. Islam first came to Northern Nigeria between the eleventh and fourteenth centuries through the trans-Sahara trade between the Hausa people of Northern Nigeria and merchants from the Maghreb states. Besides the exchange of tangible commodities, there was also a diffusion of cultural and religious values (Falola & Heaton 2008, pp. 244-246). Islam gained a stronger foothold in the region between 1804 to 1808, when a cleric of Fulani ethnicity, Usman dan Fodio, launched a jihad against the rulers of the Hausa kingdoms. The jihad led to the establishment of the Sokoto Caliphate, which consisted of several emirates. The caliphate was in existence for a century until its conquest by British forces at the beginning of the 20th century (Kirk-Greene 1965, pp. 43-44). Alhough Christianity in Nigeria can be traced to the fifteenth century when Portuguese slave traders visited Nigeria's Southernmost parts, it was not until the 1840s that the religion started to gain a foothold, propagated by freed slaves from Sierra Leone and missionaries from the West (Falola & Heaton 2008, p. 87; Ogunsola 1974, pp. 3-5).

Christian missionary evangelization was concentrated in Southern Nigeria because the Muslim rulers in the Northern Region, in an effort to preserve their religious way of life, forbade Christian

[1] Although Nigeria has 250 ethnic groups, it has three major ones: The Hausa/Fulani who are predominantly Muslim and mainly reside in Northern Nigeria. The Igbo and the Yoruba constitute the major ethnic groups in Southern Nigeria. The Igbos are predominantly Christian, while the Yoruba population is almost evenly split between Muslims and Christians (Laitin 1986).

proselytization in the region (Albert 1996, pp. 88-89). The British government did not change much in Northern Nigeria after capturing it. They appropriated the existing institutions and even used the local Hausa language in administering the Northern protectorate. Conversely, the policies of Westernization and Christianization were pursued fervently in the Southern Protectorate because its population there was more open to Western influence (Campbell & Page 2018, p. 78; Diamond 1988, p. 26; Coleman 1958, p. 333). After Nigeria's independence from British colonial rule in 1960, it remained divided along ethnic and religious lines. Commenting on the Northern-Southern dichotomy, Coleman (1958, p. 351) observed: "Certain basic underlying differences in history, culture, temperament, and levels of development and acculturation provided the classical setting for intergroup friction."

Present-day Nigeria remains polarized along ethnic and religious lines (Tuki 2023; Agbiboa 2013). Nigerians define their identity "by affiliation to religious and ethnic groups rather than the Nigerian state." (Agbiboa & Maiangwa 2013, p. 281). Nigeria has also witnessed a high incidence of violent conflicts during the past two decades, some of which were ethnically- and religiously-motivated. Data from the Armed Conflict Location and Events Database (ACLED) (Raleigh et al. 2010) shows that Nigeria had the third highest incidence of violent conflict in Africa between 1997 to 2022; only Somalia and the Democratic Republic of Congo performed worse. Despite these characteristics, no study, to the best of my knowledge, has examined how exposure to violent conflict influences hostility towards ethnic and religious outgroups using representative survey data for Nigeria, nor the heterogenous effects of violent conflict on outgroup hostility among Nigeria's Christian and Muslim populations. This study does so.

To measure outgroup hostility, I developed an additive indicator by combining the responses to two survey items probing the respondents' willingness to have people from a different religion and people from a different ethnic group as neighbors. To measure exposure to violent conflict, I drew buffers with a radius of 30km around the respondents' dwellings using QGIS software and counted the total number of violent conflicts within them. I was able to do that because I relied on the Afrobarometer (BenYishay et al. 2017) and ACLED (Raleigh et al. 2010) datasets, both of which are georeferenced. Causal identification stemmed from instrumenting exposure to violent conflict with forest cover. The regression results show that among the Nigerian population and among Christians, violent conflict has a positive effect on outgroup hostility. A plausible mechanism behind this finding is that the threat of violent conflict strengthens ingroup cohesion, erodes trust in outgroup members, and makes intergroup boundaries salient. This is especially so when the opposite party to the conflict constitutes a distinct cultural outgroup. The main conflict affecting Christians involve nomadic herders of Fulani ethnicity, who are Muslims. Compared to Muslims, Christians are more likely to associate Muslims with extremism. Among Muslims, violent conflict had a weak positive effect on outgroup hostility that was not robust to alternative estimation methods. A possible reason for this finding is that the main conflict affecting Muslims – the *Boko Haram* insurgency – does not involve Christians. Many Muslims have also been affected by conflicts involving nomadic Fulani pastoralists.

This study contributes to the broader literature on intergroup relations in the shadow of violent conflict (e.g., Schutte et al. 2023, 2022; Tuki 2023; Whitt et al. 2021; Calvo et al. 2020; Ferwerda et al. 2017). The subsequent sections are organized as follows: Section 2 reviews the literature on the nexus between conflict and social cohesion. Section 3 discusses the trend of violent conflicts in Nigeria. Section 4 operationalizes the variables that will be used to estimate the regression model and discusses the empirical strategy. Section 5 presents the regression results and discusses them, while section 6 summarizes the paper and concludes.

2.0. Theoretical considerations

Some studies have shown that exposure to violent conflict could foster social cohesion among ingroup members. In a study conducted in Nepal, Gilligan et al. (2014) found that communities exposed to violent conflict had higher levels of ingroup trust and prosocial behavior than those that were not. The mechanism behind this finding was that community members who were not socially oriented fled the conflict zone leaving behind those who were more socially oriented. Moreover, the common threat posed by conflict prompted community members to band together so they could better cope. Calvo et al. (2020) conducted a study in Mali where they found that conflict exposure had a positive effect on prosocial behavior. Although they acknowledged that social cohesion could foster post-conflict recovery, they pointed out that in the case of Mali this was problematic because increased social participation was observed only in family and ethnically homogenous associations – i.e., "inward-looking associations." This reinforced kinship ties, made ethnic fault lines salient, and heightened the risk of further conflict. Rohner et al. (2013) had a similar finding in a study conducted in Uganda where they found that conflict exposure strengthened cohesion within ethnic ingroups.

Conflict could also erode social cohesion. Weidmann and Zürcher (2013, p. 3) found that violent conflict fostered divisions in Afghan communities because it "could introduce shifting loyalties to the fighting parties and thus introduce new internal cleavages." Relying on survey data collected from members of the Tamil ethnic group in Sri Lanka, Greiner and Filsinger (2022) found that men who had been victims of sexual violence during the Sri Lankan Civil War were distrustful of both members of their ethnic group and the ethnic outgroup – i.e., the Sinhalese. Conversely, women who had been victims of sexual violence were distrustful of their ethnic ingroup and had higher levels of trust in the ethnic outgroup. They explained the erosion of ingroup trust on the grounds that "The conflict was characterized by a climate of distrust due to denunciations and betrayal within Tamil communities with harmful consequences for in-group cohesion." (p. 2). Using representative survey data for Pakistan, Ahmad and Rehman (2022) found that exposure to terrorist attacks correlated negatively with interpersonal trust. Rohner et al. (2013) had a similar finding in Uganda where they found that conflict exposure reduced generalized social trust. In a study conducted in Nigeria, Tuki (2023) showed that exposure to conflicts involving nomadic Fulani pastoralists led to distrust of both members of the Fulani ethnic group and Muslims. This was because the Fulani pastoralists were Muslims and the population tended to conflate Fulani ethnicity with being Muslim.

When the perpetrators of violence belong to a distinct cultural outgroup (e.g., based on ethnicity or religion), ingroup members might associate the entire outgroup with violence even if only a few of them were involved in the act, a phenomenon that Hall et al. (2021) referred to as the "better safe than sorry approach." This perception of threat might make ingroup members reluctant to have outgroup members as neighbors. Ahmed (2019) showed how the terrorist attack that occurred in the US on September 11th 2001 altered perceptions towards British Muslims in the UK. The ensuing "War on Terror" policy shifted the British government's focus from the diverse Asian identity of British Muslims to their religious identity, which portrayed them as a "suspect community" and associated them with terrorism. Like he concisely put it, "it is the Muslim in British Muslim which now shapes the concrete policies which govern British Muslims." (Ahmed 2019, p. 593). Ferwerda et al. (2017) conducted an experimental study in the US where they found that the association of Muslim refugees with terrorism reduced support for refugee resettlement both within the US and within the communities where the participants resided. Their analysis also showed that exposing subjects to counter frames that challenged the portrayal of refugees as threats had no statistically significant effect on support for refugee resettlement. This indicates that negative attitudes towards cultural outgroups, once formed, tend to persist.

In a study conducted in Kenya, Schutte et al. (2022) found that indiscriminate violence caused fear of religious outgroups, strengthened ingroup cohesion, and led to increased calls for residential segregation along religious lines. Moreover, they found that attacks perpetrated by Islamist insurgents led to distrust of Muslims. In another study conducted in India, Schutte et al. (2023) found that conflict not only caused prejudice towards religious outgroups and strengthened ingroup cohesion, but also increased support for extremist activities perpetrated by ingroup members. Using experiments, Obaidi et al. (2018) have shown that the perceived cultural threat posed by Muslims leads to increased support for the persecution of the Muslim outgroup among the Swedish and Danish populations. They also found a similar effect among Muslims who view Western culture as decadent and a threat to Islam. Conversely, Whitt et al. (2021) conducted an experimental study in Syria, Bosnia and Kosovo where they found that hostile attitudes towards outgroups tend to change following productive interactions between the two groups. This is consistent with the premise of the contact hypothesis put forth by Allport (1954) that intergroup contact, conditional upon cooperation towards a common goal and equality between the groups, reduces prejudice.

Returning to the Nigerian case, I expect conflict exposure to have a positive effect on outgroup hostility among the population, especially because of how polarized the country is along ethnic and religious lines. However, there might be heterogenous effects among Christians and Muslims: As will be discussed in the subsequent section, the main conflict affecting Muslims involve the Islamist group *Boko Haram*. It is thus likely that conflict exposure would have no effect on hostility towards ethnic and religious outgroups since the outgroup, which is mainly Christian, is not associated with *Boko Haram*. Among Christians, conflict exposure is likely to have a positive effect on outgroup hostility because the major conflict affecting Christians – i.e., the violent clashes between nomadic Fulani pastoralists who are Muslim and sedentary farmers, most of who are Christians – is often viewed through a religious lens (Parsons 2023; Christian Association of Nigeria 2018). Moreover, Fulani pastoralists tend to be perceived as a "suspect community" with a high predisposition to violence (Ejiofor 2022; Eke 2020). This study will test the following hypotheses:

H_1: Among Nigerians, conflict exposure leads to outgroup hostility.

H_2: Among Christians, conflict exposure leads to outgroup hostility.

H_3: Among Muslims, conflict exposure has no effect on outgroup hostility.

3.0. Violent conflicts in Nigeria

Nigeria has witnessed a lot of violent conflicts during the past two decades. Data from ACLED

(Raleigh et al. 2010) shows that Nigeria had a total of 18,781 incidents between 1997 to 2022, which makes it the country with the third highest incidence of violent conflict in Africa. Only Somalia and the Democratic Republic of Congo performed worse.[2] These incidents caused 98,877 fatalities. The distribution of violent conflict incidents varies across Nigeria's two regions: 68 percent of them occurred in Northern Nigeria while the remaining 32 percent occurred in the Southern Region. The conflicts are also spread unevenly across the years from 1997 to 2022, with 91 percent of them occurring between 2009 to 2022.

The two major conflicts affecting Nigeria are the *Boko Haram* insurgency and the violent clashes between Muslim nomadic herders of Fulani ethnicity and sedentary farmers who are mostly Christians. A report by the Institute of Economics and Peace (2019, p. 21) noted: "In Nigeria, terrorist activity is dominated by Fulani extremists and Boko Haram. Together, they account for 78 per cent of terror-related incidents and 86 per cent of deaths from terrorism." The incidence of violent conflict in Nigeria can roughly be broken down into two epochs: Pre- and post-*Boko Haram* era. The pre-*Boko Haram* era covers the period from 1997 to 2008 before *Boko Haram* started its insurgency. The post-*Boko Haram* era covers the years from 2009 onwards after *Boko Haram* launched its first attack. The *Boko Haram* insurgency ushered Nigeria into a phase of violence it had never witnessed. Between 2009 to 2022, there were 4,776 incidents where at least one of the parties to the conflict was *Boko Haram*. These incidents caused a total of 43,019 fatalities. Because *Boko Haram* attacks are concentrated in Northeastern Nigeria where the population is predominantly Muslim (see figure 1), most of the casualties from *Boko Haram* attacks are Muslims.

[2] Based on the ACLED dataset, I define violent conflicts as incidents categorized under any of the following three categories: Battles, Violence against civilians, and Explosions/Remote violence. This implies that I have excluded incidents categorized as Riots, Protests, and Strategic developments.

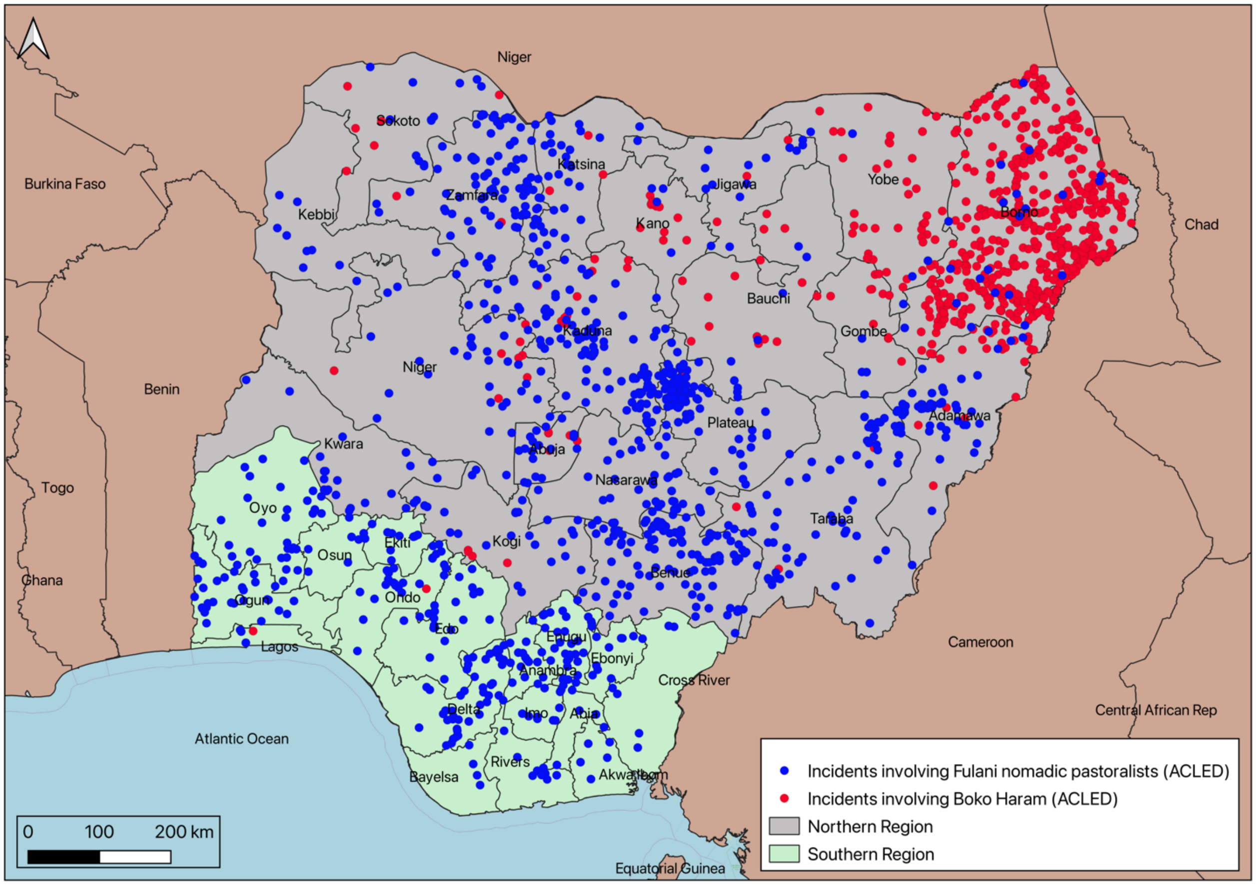

Figure 1: Incidents involving Boko Haram and nomadic Fulani pastoralists (1997 – 2022).

Note: The figure shows the administrative boundaries of the states that constitute Nigeria's Northern and Southern Regions. The red dots show the geolocations of conflicts where at least one of the actors is *Boko Haram. The* blue dots show the geolocations of conflicts where at least one of the actors is a "Pastoralist" or belongs to the "Fulani" ethnic group. Virtually all the actors defined as pastoralists in the ACLED dataset are identified as "Fulani Ethnic militia," which makes the two terms almost synonymous. Although Northern Nigeria has a predominantly Muslim population, there are a few states there like Benue and Plateau, where the population is predominantly Christian and Muslims constitute a very small minority. These two states, which were not captured by the Muslim jihadists in the early 19th century, have the highest incidence of conflicts involving nomadic Fulani pastoralists. The shapefiles containing Nigeria's administrative boundaries was developed by UNOCHA and could be accessed here: https://data.humdata.org/dataset/nga-administrative-boundaries

Nigerians tend to associate Muslims with extremism. The Round 7 Afrobarometer survey (BenYishay et al. 2027) conducted in 2017, and which is representative for Nigeria's population, had a question where respondents were asked about the degree to which they thought Muslims supported extremist groups. 26 percent of them chose the "none" response category, 37 percent chose the "some of them" response category, 24 percent chose the "most of them" response category, 7 percent chose the "all of them" response category, while the remaining 6 percent did not answer the question. This suggests that 68 percent of Nigerians associate Muslims with extremism at least to some degree.

Disaggregating the data based on religious affiliation showed that 84 and 48 percent of Christians and Muslims respectively associated Muslims with extremism at least to some degree.

The violent clashes between nomadic Fulani pastoralists and sedentary farmers are the second major conflict affecting Nigeria. This conflict, which is primarily caused by competition over land and water resources between the two actors, has quickly taken a religious turn because of the distinct ethnic and religious identities of the opposing parties. Some reports have portrayed farmer-pastoralist conflicts as attacks on Christians by Muslims because the pastoralists are Muslims and majority of the sedentary population is Christian. Moreover, Christians are overrepresented among the victims of these conflicts (Parsons 2023; Christian Association of Nigeria 2018). Relying on large-N survey data collected from Kaduna, the state with the third highest incidence of farmer-pastoralist conflicts in Nigeria, Tuki (2023) found that Christians and Muslims view the conflict differently: 52 percent of Christians agree that farmer-pastoralist conflicts are caused by religion; only 17 percent of Muslims hold this view. Data from ACLED (Raleigh et al. 2010) shows that between 1997 to 2022, there were 2,416 violent conflicts where at least one of the actors was a pastoralist or belonged to the Fulani ethnic group. These incidents caused a total of 15,333 fatalities. As shown in figure 2, incidents involving nomadic Fulani pastoralists, unlike *Boko Haram* attacks, are spread across all of Nigeria's 36 states. This is due to the migratory nature of pastoralists in search of pasture for their livestock.

4.0. Data and methodology

This study relies on the Round 7 Afrobarometer survey data (BenYishay et al. 2017) collected in 2017.[3] The dataset consists of 1,600 observations and is representative for Nigeria. Respondents were drawn from each of Nigeria's 36 states and the federal capital territory – Abuja. Of Nigeria's 774 local government areas (LGAs) (i.e., municipalities), data were collected from 147 of them. The respondents were at least 18 years old, with males and females equally represented in the sample.

[3] To access the Afrobarometer dataset and the survey questionnaire visit: https://www.afrobarometer.org/

4.1. Operationalization of the variables

4.1.1. Dependent variable

Outgroup hostility: This is an additive indicator that measures the respondents' willingness to have people from other religions and other ethnic groups as neighbors. It was derived by combining the responses to the following questions: "For each of the following types of people, please tell me whether you would like having people from this group as neighbors, dislike it, or not care: (a) People of a different religion; (b) People from other ethnic groups," with the responses measured on a five-point ordinal scale ranging from "1 = strongly like," to "5 = strongly dislike." The additive indicator ranges from 2 to 10.[4] I treated the "don't know" and "refused to answer" responses as missing observations. I applied this rule to all the variables derived from the Afrobarometer survey.

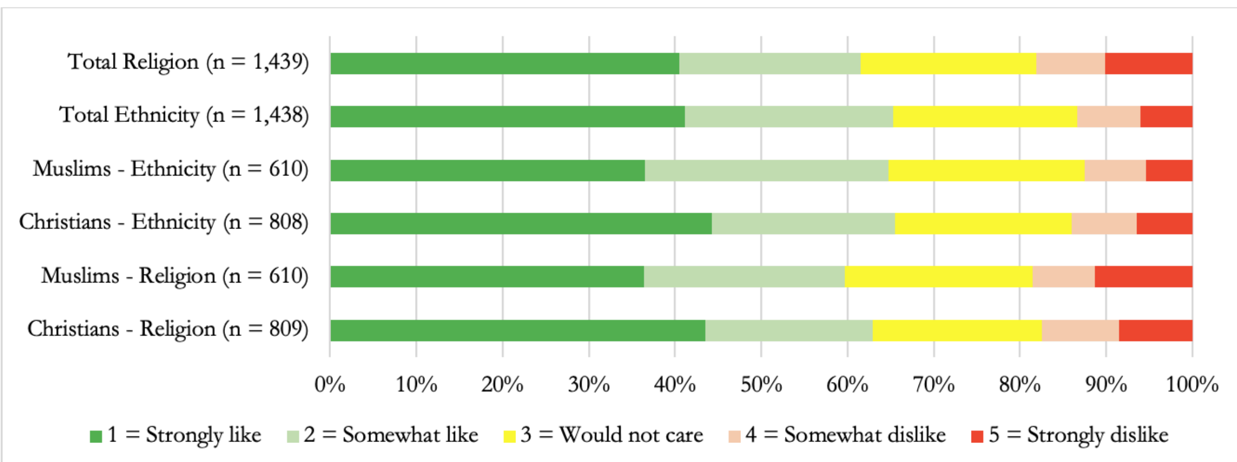

Figure 2: Hostility towards ethnic and religious outgroups

Note: The y-axis shows the total number of respondents in the full sample, and the number of Muslim/Christian respondents who had answered the relevant question regarding their willingness to have people from a different religion and ethnic group as neighbors. The x-axis shows the percentage of respondents who chose a particular response category.

The two survey items had a Cronbach Alpha statistic of 0.84, which shows internal consistency. The two items also had a correlation of 0.72, which highlights the close association between ethnicity and religion in Nigeria. As shown in the first two bar charts from the top of figure 2, Nigerians have a

[4] In the original Afrobarometer dataset, higher ordinal values denote a lower level of outgroup hostility and vice versa. For easy interpretation of the regression results, I inverted the ordinal values assigned to the response categories by subtracting each of them from 6, which allowed higher (lower) values to denote a higher (lower) level of outgroup hostility.

slightly higher level of hostility towards religious outgroups than ethnic outgroups. Christians are slightly more hostile towards people of a different ethnic group than Muslims. Muslims are slightly more hostile towards people of a different religion than Christians. Both Christians and Muslims are more hostile towards people of a different religion than people of a different ethnic group.

4.1.2. Explanatory variable

Violent conflict: This measures the total number of violent conflict incidents within the 30km buffer around the respondents' dwellings. I developed the buffers using QGIS software. This was possible because I relied upon the Afrobarometer (BenYishay 2017) and ACLED (Raleigh et al. 2010) datasets, both of which are georeferenced.

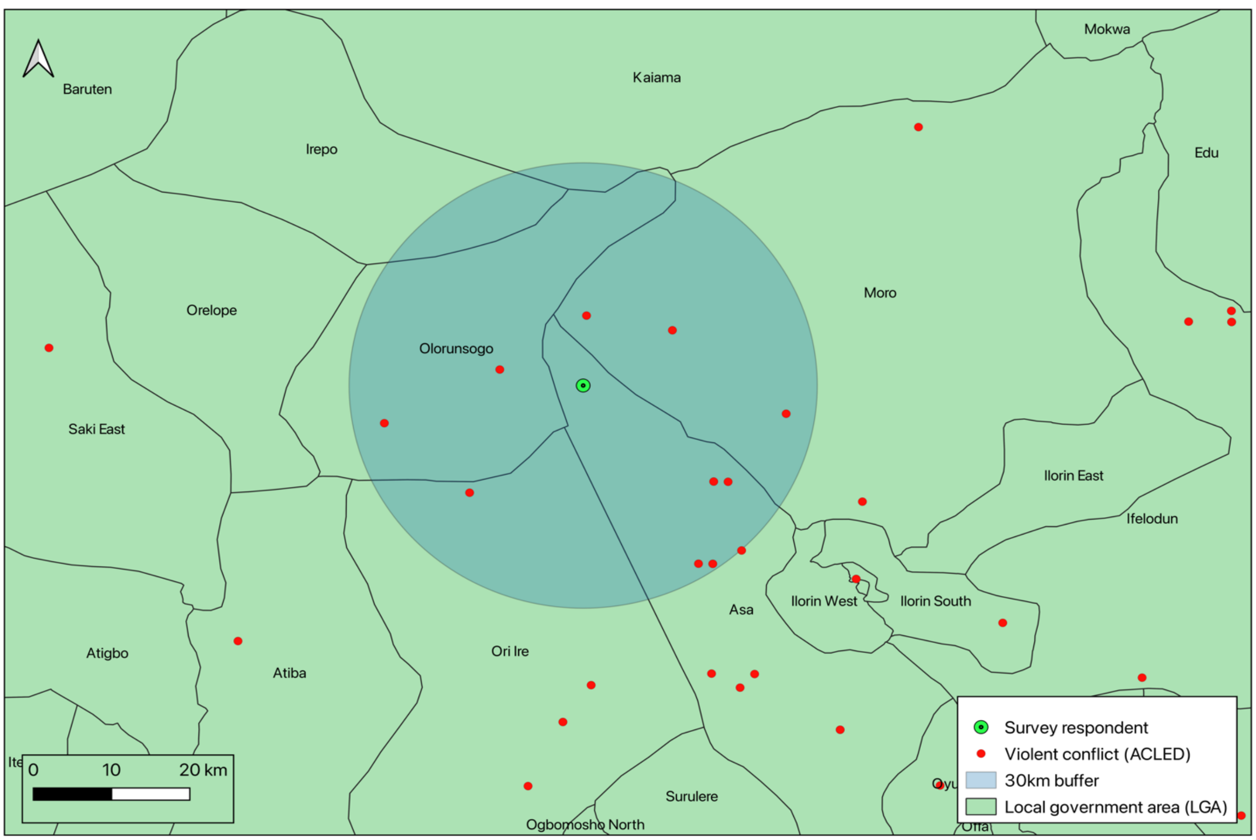

Figure 3: Measuring exposure to violent conflict

Note: Using a single respondent for a demonstrative purpose, the figure shows the 30km buffer around his/her dwelling. It also shows the geolocations of the violent conflicts and the local government area (LGA) (i.e., municipality) administrative boundaries.

Based on the ACLED dataset, I define violent conflicts as incidents that fall under any of the following categories: Battles, Violence against civilians, and Explosions/Remote violence.[5] Although the ACELD dataset is available starting from 1997 and is updated in real time, I excluded conflict incidents that occurred after 2016. This lags the explanatory variable since the dependent variable is measured in 2017. I considered all the incidents within the buffer from 1997 to 2016 because I am particularly interested in the cumulative effect of violent conflict. Some studies have shown that memories from past conflicts tend to persist and could shape action in the present (Wagoner & Brescó 2016; Tint 2010).

Buffers are a more efficient way of measuring exposure to violent conflict than the LGA administrative boundaries. This is because the spatial area occupied by each buffer is unique for each respondent and allows for more variation in the conflict exposure variable. If I had measured conflict exposure at the LGA level, I would have associated all the respondents residing within a particular LGA with the total number of conflict incidents there, which presumes that all respondents residing within a particular LGA are equally exposed to violent conflict. This would have been inefficient because incidents in a contiguous LGA might be nearer to a respondent's dwelling than those in the particular LGA where he/she resided. As shown in figure 3, the respondent resides in Asa LGA, yet conflicts in Moro, Olorunsogo, and Ori Ire LGAs are closer to his/her dwelling than some incidents in Asa LGA. Another challenge that comes along with working with Nigeria's administrative boundaries (especially those at the lower levels) is that they are not clearly defined. In fact, there were a few observations where respondents residing close to Nigeria's national border were more exposed to conflicts in the contiguous countries of Cameroon, Chad, Benin, and Niger than those within the particular Nigerian state or LGA where they resided. The use of buffers, which disregards administrative boundaries, attenuates these problems. 96 percent of the respondents had at least one violent conflict incident within the 30km buffer around their dwellings. 31 percent of them had at least

[5] To access the ACLED dataset visit: https://acleddata.com/

50 incidents.

4.1.3. Control variables

I considered some objective control variables for economic performance, poverty, and population size. I also controlled for the respondents' educational level and demographic attributes. The control variables and the rationale for their inclusion in the regression models are discussed below:

Population size: This measures the total number of people residing within the 30km buffer around the respondents' dwellings in 2016. I controlled for population size because it could influence both the dependent and explanatory variables. The dispersion pattern of a population could influence the risk of conflict. When the population is scattered along the edges of a country rather than being concentrated in an area, for instance due to a rough geographical terrain, this limits the capacity of the state to exert control over the polity, which in turn increases the risk of conflict (Herbst 2000; Collier & Hoeffler 2000). The size of the population might also be proxying the level of urbanization. Some studies have found that populations in urban centers have a higher level of outgroup trust than those in rural areas (Xu 2021; Delhey & Newton 2005). Since the raw population dataset is gridded, I computed the relevant statistic for the buffers using QGIS software. The raster data for population was obtained from Worldpop at the University of Southampton.[6]

Nighttime light: This measures the mean annual nighttime light pixels within the 30km buffer around the respondents' dwellings in 2016 (Ghosh et al. 2021). This variable proxy the level of economic activity. Slow economic growth has been found to increase the risk of conflict (Collier 2008). Economic decline and rising inequality also correlate negatively with outgroup trust. This is because people become risk aversive and associate interactions with outgroup members with higher risk (Stewart et al. 2020; Delhey & Newton 2005). I computed the relevant statistic for the buffers using

[6] To access the population dataset visit: https://www.worldpop.org/

QGIS software because the raw nighttime light dataset is gridded. The pixel range for this variable is from 0 to 63, with higher values denoting a higher level of economic activity and vice versa. Source: Earth Observation Group database.[7]

Prevalence of stunting: This measures the proportion of children under the age of 5 within the 30km buffer around the respondents' dwellings who were classified as stunted in 2013 (Bosco et al. 2017). This variable proxy the socioeconomic wellbeing of the population. Some studies have shown that poverty causes conflict (Braithwaite et al. 2016; Do & Iyer 2010). Poverty also correlates negatively with social trust (Gereke et al. 2018; Alessina & La Ferrara 2000). Since the raw dataset is gendered and also gridded, I computed the relevant statistic within the buffers for both males and females using QGIS software and then took the average. Unlike the datasets for violent conflict, nighttime light, and population size, which are available for Nigeria and the contiguous countries bounding it, the prevalence of stunting dataset is available only for Nigeria's administrative boundaries. This implies that for the 120 respondents (i.e. 7.5 percent of the 1600 observations) whose buffers encroach into the contiguous countries, I computed the relevant statistic for only the buffers' spatial area within Nigeria's administrative boundary. Source: Worldpop Development and Health Indicators database.[8]

Educational level: This measures the educational attainment of the respondents on a nine-point ordinal scale ranging from "0 = no formal schooling" to "9 = postgraduate." People who are educated might be more accommodating towards outgroups than their uneducated counterparts because education exposes them to diverse ideas (Ferwerda et al. 2017; Jenssen & Engesbak 1994). Education could reduce the risk of violent conflict by increasing the opportunity cost of rebel participation (Collier & Hoeffler 2000).

Demographic covariates: This includes the age, gender, and religious affiliation of the respondents.

[7] To access the nighttime light dataset visit: https://eogdata.mines.edu/products/dmsp/
[8] To access the prevalence of stunting dataset visit: https://hub.worldpop.org/geodata/summary?id=1268

Religious affiliation is measured using a dummy variable that takes a value of 1 if the respondent identifies as Christian and 0 if Muslim. I derived the binary variable by collapsing the various Christian and Muslim denominations into singular categories. Gender is measured using a dummy variable that takes the value of 1 if the respondent is male and 0 if female.

4.2. Empirical strategy

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

$$y_t = \beta_0 + \beta_1 Violent\ conflict_t + \beta_2 X'_t + e_t$$

Where y_t is the dependent variable which measures hostility towards ethnic and religious outgroups at time t, X'_t is a vector of control variables that have been discussed in the preceding section, β_0 is the intercept, β_1 and β_2 are the coefficients of the explanatory and control variables respectively, and e_t denotes the error term.

While the model estimates the effect of exposure to violent conflict on outgroup hostility, the reverse is also possible: People with a high level of outgroup hostility might be those who are exposed to violent conflict. This leads to the problem of reverse causality. To mitigate this problem, I have lagged the explanatory variable by considering only conflict events that occurred before 2017 since the dependent variable is measured in 2017. However, omitted variable bias might still be a problem because there could be some variables in the error term that influence outgroup hostility which I may not have controlled for in the regression model. To address this problem, I adopted an instrumental variable approach and estimated the model using two-stage least squares (2SLS) regression.

I used forest cover as an instrumental variable for violent conflict. I expect that forest cover would plausibly not directly influence hostility towards ethnic and religious outgroups, except through the mechanism of violent conflict. Some studies have shown that forest cover could increase the risk of conflict by providing strategic military advantages to insurgent groups (Schaub & Auer 2022; Do & Iyer 2010). In the state of Borno, which is located in Northeastern Nigeria, *Sambisa Forest* has served as a fortress for *Boko Haram* insurgents. In 2014 *Boko Haram* insurgents kidnapped over 200 girls from a boarding school in the town of Chibok and held them captive in the forest (Kayode 2014; Grill & Selander 2014). In 2021 gunmen abducted about 300 girls from a boarding school in the state of Zamfara and held them hostage in the forest. The girls were later released after negotiations between the state government and the abductors (Akinwotu 2021).

To measure forest cover, I computed the proportion of land area within the 30km buffer around the respondents' dwellings that consists of forests. More specifically, I derived the forest variable by dividing the total forest pixels within the 30km buffer by the total land cover pixels. The raw dataset was obtained from the Global Land Cover (GlobCover) dataset, which classifies the land area across the globe into 22 categories (Bontemps et al. 2011).[9] I define forests as pixels ranging from classes 20 to 120. I relied on the 2009 version of the GlobCover dataset, which is the most recent. Since the raw dataset is gridded, I computed the relevant statistics for the buffers using QGIS software.

4.3. Summary statistics and analytical technique

Table 1: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Outgroup hostility$^{\phi}$	1437	4.389	2.351	2	10
Outgroup hostility (religion)	1439	2.261	1.331	1	5
Outgroup hostility (ethnicity)	1438	2.13	1.202	1	5
Violent conflict$^{\#}$	1592	67.886	106.807	0	475
Nighttime light$^{\#}$	1592	3.1	5.191	0	20.104
Prevalence of stunting$^{\#}$	1592	0.331	0.147	0.136	0.634
Log Population size$^{\#}$	1592	14.032	1.116	11.536	16.39
Educational level	1445	4.513	2.155	0	9
Religious affiliation	1428	0.569	0.495	0	1
Gender	1448	0.501	0.5	0	1
Age	1447	32.658	12.428	18	80
Forest cover	1592	0.599	0.223	0.056	0.985
(Forest cover)^2	1592	0.408	0.26	0.003	0.969

Note: *ϕ is the dependent variable which is derived by adding "Outgroup hostility (religion)" and "Outgroup hostility (ethnicity)," # denotes variables measured using buffers with a radius of 30km. Although the Afrobarometer dataset has 1,600 potential observations, the variables in the table contain fewer observations because not all respondents were asked the relevant questions. Also, I treated all "don't know" and "refused to answer" responses as missing observations which may have exacerbated the problem of listwise deletion.*

Table 1 presents the summary statistics of the variables that will be used to estimate the

[9] To access the GlobCover dataset and the codebook/validation report visit: http://due.esrin.esa.int/page_globcover.php

regression models.

5.0. Results and discussion

5.1. First-stage regressions

Table 2: Association between forest cover and violent conflict

Violent conflict$^{\#\phi}$	(1) All data	(2) North	(3) South	(4) All data	(5) All data
Forest cover$^{\#}$	-34.281***	44.645***	-222.468***		339.491***
	(11.983)	(15.742)	(17.276)		(58.777)
(Forest cover)$^{2\#}$				-42.075***	-327.394***
				(10.254)	(50.43)
Constant	88.418***	13.732	249.504***	85.069***	-1.74
	(7.658)	(8.593)	(12.366)	(4.963)	(15.812)
Observations	1592	772	820	1592	1592
R-squared	0.005	0.01	0.169	0.01	0.031

Note: *ϕ is the dependent variable, standard errors are in parenthesis, *** p<0.01, ** p<0.05, * p<0.10. # denotes variables measured using buffers with a radius of 30km. All models are estimated using ordinary least squares (OLS) regression.*

Table 2 presents the results of ordinary least squares (OLS) regression models examining the relationship between forest cover and violent conflict. In model 1, forest cover was significant at the one percent level and carried a negative sign. This result is incongruent with the a priori expectation that forest cover increases the risk of conflict. However, this *anomalous* finding might not necessarily be wrong, especially when Nigeria's topography and the distribution of violent conflicts across the country are considered. As was mentioned in section 3, over two-thirds of all violent conflicts that occurred in Nigeria between 1997 to 2022 were in the Northern Region, while the remaining one-third were in the Southern Region. The Northernmost part of Nigeria is proximate to the *Sahara Desert* and has a dry climate. The land there is also arid with sparse vegetation. The southernmost part of Nigeria is contiguous to the Atlantic Ocean, and a large swathe of the land area there falls within the rainforest vegetation zone. The amount of rainfall and vegetation cover in Nigeria increases as one moves southwards from the north.

Given this background, the negative correlation between forest cover and the incidence of conflict in model 1 should not be surprising. The forests in Northern Nigeria might be more hospitable for insurgents because they are not as dense as those in Southern Nigeria. If this logic holds, then I should find a positive correlation between forest cover and violent conflict when I estimate a model using the subsample of observations in Northern Nigeria. Conversely, I should find a negative correlation between forest cover and violent conflict when I estimate a model using the subsample of observations in Southern Nigeria because the denseness of the forests in the Southernmost parts of the region would make them inhospitable for insurgent groups. As shown in model 2 which was estimated using the subsample of observations in Northern Nigeria, forest cover carried a positive sign. In model 3, which was estimated using the subsample of observations in Southern Nigeria, forest cover carried negative sign.

Given the above patterns, it is possible that a quadratic specification might better capture the relationship between forest cover and violent conflict. This is because both vegetation extremes – its total absence and abundance – are unsuitable for insurgent groups, which in turn reduce the risk of violent conflict. If this is indeed the case, then the square of forest cover should carry a negative sign when regressed on violent conflict, suggesting an inverse quadratic relationship akin to an inverted "U". As shown in model 4, this is the case. This is consistent with the findings of Chow and Han (2023). I estimated a final model where I considered both forest cover and its square together. As shown in model 5, the negative sign accompanying the square of forest cover persists. Taking into consideration Nigeria's climate, vegetation cover, and the spatial distribution of violent conflicts across the country, I use both forest cover and its square as instrumental variables.[10]

5.2. Second-stage regressions

Table 3 reports the second-stage regression results of models examining the effect of exposure to violent conflict on hostility towards ethno-religious outgroups. In model 1 – the baseline model – I included only the explanatory variables and fixed effects for all the ethnic groups.[11] Violent conflict was significant at the five percent level and carried the expected positive sign. This indicates that

[10] I also estimated some 2SLS regression models where I used either forest cover or its square as instrumental variables. The second-stage regression results were consistent with those that have been reported in section 5.2.

[11] Table A5 in the appendix shows the ethnic distribution of the respondents in the Afrobarometer dataset

exposure to violent conflict has a positive effect on hostility towards ethno-religious outgroups. This is consistent with my earlier hypothesis that Nigerians who are exposed to violent conflict would be hostile towards ethnic and religious outgroups. This is because Nigeria is polarized along ethnic and religious lines. Moreover, conflict exposure fosters ingroup cohesion, erodes trust in outgroup members, and makes ingroup members less accommodating of outgroup members.

Table 3: Effect of violent conflict on outgroup hostility I

Outgroup hostility$^{\phi}$	Full sample		Religious subsamples		
	(1)	(2)	(3) Xtian	(4) Muslim	(5) Muslim
Violent conflict#	0.004**	0.025***	0.046***	0.007	0.002*
	(0.002)	(0.007)	(0.012)	(0.009)	(0.001)
Nighttime light#		-0.435***	-0.862***	-0.106	-0.037
		(0.117)	(0.204)	(0.117)	(0.033)
Prevalence of stunting#		3.623***	-3.081	4.252*	2.951***
		(1.225)	(1.89)	(2.365)	(0.996)
Log Population size#		-0.023	0.234	-0.095	0.032
		(0.133)	(0.209)	(0.247)	(0.135)
Educational level		-0.19***	-0.004	-0.199***	-0.183***
		(0.038)	(0.057)	(0.05)	(0.043)
Religious affiliation		0.406*			
		(0.235)			
Gender		-0.339***	0.046	-0.895***	-0.901***
		(0.13)	(0.175)	(0.176)	(0.18)
Age		-0.009	-0.008	-0.005	-0.003
		(0.005)	(0.007)	(0.008)	(0.006)
Constant	4.828***	4.118**	2.284	5.057**	3.983**
	(0.127)	(1.706)	(3.353)	(2.482)	(1.779)
Estimation method	2SLS	2SLS	2SLS	2SLS	OLS
Ethnic group fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1437	1413	806	607	607
R-squared	0.132			0.168	0.187
Durbin statistic	9.235***	13.504***	17.062***	0.389	
Wu-Hausman statistic	9.1***	13.277***	16.718***	0.375	
Sargan statistic	0.092	0.011	1.605	3.82*	
Basmann statistic	0.09	0.011	1.542	3.705*	

Note: *ϕ is the dependent variable, standard errors are in parenthesis, ***p<0.01, **p<0.05, *p<0.10. # denotes variables measured using buffers with a radius of 30km. All models are estimated using two-stage least squares (2SLS) regression, except for model 6 which is estimated using OLS regression.*

In model 2 where I added the control variables, violent conflict retained its positive sign and its significance level increased to one percent. The effect size also increased from 0.004 to 0.025. To check whether endogeneity was indeed present, I conducted a test. As shown in the lower panel of the table, the Durbin and Wu-Haussman statistics were both significant at the one percent level, which indicates that the use of an instrumental variable estimation technique was appropriate. To check for the suitability of the instrumental variables, I conducted a test for over-identifying restrictions – since I have two instrumental variables and only one endogenous variable, which makes the model over-identified. Both the Sargan and Bassman statistics were statistically insignificant, which suggests that the instrumental variables are appropriate.

To check for heterogenous effects based on religious affiliation, I estimated models using the Christian and Muslim subsamples of respondents. As shown in model 3 which was estimated using the Christian subsample, violent conflict carried a positive sign and was significant at the one percent level. This indicates that among Christians, conflict exposure leads to hostility towards ethno-religious outgroups. This is consistent with my earlier hypothesis. A plausible reason for this finding among Christians is that the major conflict affecting them involves nomadic Fulani pastoralists who are Muslims and constitute a unique cultural outgroup. Christians also tend to view the conflict through a religious lens (Parsons 2023; Christian Association of Nigeria 2018). The Round 7 Afrobarometer also shows that compared to Muslims, Christians are more likely to associate Muslims with extremism. Such perceptions catalyze polarization and increase the reluctance of Christians to have members of ethno-religious outgroups as neighbors. Worth highlighting is that the size of the coefficient in model 3 is larger than that in model 2, which suggests that exposure to violent conflict has a larger effect on hostility towards ethno-religious outgroups among Christians compared to the larger Nigerian population. A point worth re-emphasizing is that the operationalization for outgroup hostility employed in this study does not imply violence towards cultural outgroups, but rather the willingness to have members of the outgroup as neighbors. In model 4, which was estimated using the Muslim subsample of respondents, violent conflict was statistically insignificant. A closer examination of the results shows that the Durbin and Wu-Hausmann statistics were also insignificant, which suggests the absence of endogeneity. Moreover, both the Sargan and Basmann statistics were significant at the 10 percent level, which indicates that the instrumental variables were unsuitable. Ordinary least squares (OLS) regression, would thus be more suitable for estimating the model than 2SLS regression. As shown in model 5 which was estimated using OLS regression, violent conflict carried a positive sign and was significant at the 10 percent level. The effect size was very small compared to that in model 3 where I had used the Christian subsample of respondents. The weak positive effect among Muslims might be because the main conflict affecting them – the *Boko Haram* insurgency – does not involve Christians. A significant number of Muslims are also affected by the violent clashes with Muslim nomadic Fulani herders.

5.3. Robustness check

It is possible that the positive effect of violent conflict on outgroup hostility among the Nigerian population (i.e., models 1 and 2 in table 3) is influenced by the way that the dependent variable was operationalized. To check whether conflict exposure influences hostility towards ethnic and religious outgroups differently, I disaggregated the dependent variable and estimated models using its respective components. Since each component has five ordinal categories, I estimated the models using instrumental variable ordered probit (IVOprobit) regression, which is based on maximum likelihood estimation. Table 4 reports the results.

Models 1 and 2 examine the effect of violent conflict on hostility towards religious outgroups only. In model 1 – the baseline model – violent conflict carried a positive sign and was significant at the five percent level. This suggests that among the Nigerian population, exposure to violent conflict leads to hostility towards religious outgroups. Violent conflict retained its positive sign and its significance level increased to one percent in model 2 where I added the control variables. Keeping all covariates at their mean levels, the analysis showed that a one unit increase in the number of violent conflicts within the 30km buffer around the respondents' dwellings reduces the likelihood of them choosing the "strongly like" response category by 0.2 percent, when asked about their willingness to have people of a different religion as neighbors.[12]

[12] Table A1 in the appendix reports the marginal effects at the mean for model 2

Table 4: Regression models examining the effect of violent conflict on outgroup hostility II

Outgroup hostility$^{\phi}$	Religion		Ethnicity	
	(1)	(2)	(3)	(4)
Violent conflict#	0.003**	0.005***	0.003*	0.005***
	(0.001)	(0.001)	(0.002)	(0.001)
Nighttime light#		-0.036***		-0.03**
		(0.012)		(0.012)
Prevalence of stunting#		0.492		0.207
		(0.362)		(0.367)
Log Population size#		0.124***		0.118**
		(0.045)		(0.046)
Educational level		-0.057***		-0.064***
		(0.015)		(0.016)
Religious affiliation		0.018		0.081
		(0.088)		(0.09)
Gender		-0.158***		-0.094*
		(0.055)		(0.054)
Age		-0.002		0.00
		(0.002)		(0.002)
Estimation method	IVOprobit	IVOprobit	IVOprobit	IVOprobit
Ethnic group fixed effects	Yes	Yes	Yes	Yes
Observations	1439	1415	1438	1414
Log likelihood	-10738.622	-10521.033	-10665.251	-10454.267
Error terms correlation	-0.41***	-0.497***	-0.32*	-0.462***

Note: *ϕ is the dependent variable, standard errors are in parenthesis, *** p<0.01, ** p<0.05, * p<0.10. # denotes variables measured using buffers with a radius of 30km. All models are estimated using IV ordered probit (IVOprobit) regression. I have not reported the intercepts of the models.*

Models 3 and 4 examine the effect of violent conflict on hostility towards ethnic outgroups only. In model 3 – the baseline model – violent conflict carried a positive sign and was significant at the 10 percent level. This indicates that among Nigerians, exposure to violent conflict leads to hostility towards ethnic outgroups. In model 4 where I added the control variables, violent conflict retained its positive sign and its significance level increased to one percent. Keeping all covariates at their mean levels, the analysis showed that a one unit increase in the number of violent conflicts within the 30km buffer around the respondents' dwellings reduces the likelihood of them choosing the "strongly like" response category by 0.2 percent, when asked about their willingness to have people from a different ethnic group as neighbors.[13] Worth highlighting is that the effect size of violent conflict on hostility towards religious and ethnic outgroups are identical, which might be because of the close association

[13] Table A2 in the appendix reports the marginal effects at the mean for model 5

between ethnicity and religion in Nigeria. Suffice to add that the correlations between the error terms of the first- and second-stage regressions for all the models reported in table 4 were statistically significant, which indicates that endogeneity was present and the use of an instrumental variable approach was appropriate. When I treated all the variables as continuous and re-estimated all the models reported in Table 4 using 2SLS, the results remained consistent (See table A6 in the appendix).

I conducted some more robustness checks where I estimated models using the religious subsamples of respondents and the ethnic and religious components of outgroup hostility. Table 5 reports the results. In models 1, 2, and 3, the dependent variable measures hostility towards religious outgroups only. In model 1 which was estimated using the Christian subsample of respondents, violent conflict carried a positive sign and was significant at the one percent level. This indicates that among Christians, conflict exposure leads to hostility towards religious outgroups. Keeping all covariates at their mean levels, the analysis showed that a one unit increase in the number of violent conflicts within the 30km buffer around the Christian respondents' dwellings reduces the likelihood of them choosing the "strongly like" response category by 0.3 percent when asked about their willingness to have people from a different religion as neighbors.[14] The correlation between the error terms of the first- and second-stage regressions was significant at the one percent level, which indicates that endogeneity was present and the use of an instrumental variable approach was appropriate.

In model 2 which was estimated using the Muslim subsample of respondents, violent conflict was statistically insignificant. The correlation between the error terms of the first- and second-stage regression models was also statistically insignificant, which suggests that endogeneity was absent and the use of an instrumental variable approach to estimate the model was inappropriate. I thus re-estimated the model using ordered probit (Oprobit) regression. As shown in model 3, violent conflict

[14] Table A3 in the appendix reports the marginal effects at the mean for model 1

remained statistically insignificant. This suggests that among Muslims, conflict exposure has no effect on hostility towards religious outgroups. This is consistent with the hypothesis stated earlier.

Table 5: Regression models examining the effect of violent conflict on outgroup hostility III

Outgroup hostility$^\phi$	**Religion**			**Ethnicity**		
	(1) (Xtian)	**(2) (Muslim)**	**(3) (Muslim)**	**(4) (Xtian)**	**(5) (Muslim)**	**(6) (Muslim)**
Violent conflict#	0.007***	0.004	0.001	0.006***	0.003	0.001
	(0.001)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)
Nighttime light#	-0.076***	-0.024	-0.018	-0.049**	-0.023	-0.018
	(0.024)	(0.019)	(0.02)	(0.023)	(0.02)	(0.02)
Prevalence of stunting#	-1.029	1.597***	1.779***	-0.026	0.852	0.951*
	(0.725)	(0.581)	(0.551)	(0.716)	(0.558)	(0.555)
Log Population size#	0.208**	0.022	-0.006	0.226***	0.036	0.017
	(0.082)	(0.072)	(0.071)	(0.082)	(0.073)	(0.072)
Educational level	0.00	-0.083***	-0.087***	-0.039*	-0.075***	-0.076***
	(0.022)	(0.023)	(0.022)	(00.022)	(0.022)	(0.022)
Gender	0.008	-0.396***	-0.422***	0.083	-0.346***	-0.358***
	(0.069)	(0.101)	(0.092)	(0.069)	(0.094)	(0.092)
Age	-0.003	-0.003	-0.004	-0.001	0.002	0.002
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Estimation method	IVOprobit	IVOprobit	Oprobit	IVOprobit	IVOprobit	Oprobit
Ethnic group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	807	608	608	806	608	608
Pseudo R^2			0.072			0.052
Log likelihood	-5909.244	-4556.848	-831.695	-5872.613	-4536.603	-811.222
Error terms correlation	-0.542***	-0.357		-0.542***	-0.272	

Note: *ϕ is the dependent variable, standard errors are in parenthesis, *** p<0.01, ** p<0.05, * p<0.10. # denotes variables measured using buffers with a radius of 30km. All models are estimated using IV ordered probit (IVOprobit) regression, except for models 3 and 6 which are estimated using ordered probit (Oprobit) regression. I have not reported the intercepts of the models.*

In models 4, 5, and 6, the dependent variable measures hostility towards ethnic outgroups only. In model 4 which was estimated using the Christian subsample of respondents, violent conflict carried the expected positive sign and was significant at the one percent level. This indicates that among Christians, exposure to violent conflict has a positive effect on hostility towards ethnic outgroups. Keeping all covariates at their mean levels, the analysis showed that a one unit increase in the number of violent conflicts within the 30km buffer around the Christian respondents' dwellings reduces the likelihood of them choosing the "strongly agree" response category by 0.3 percent when asked about their willingness to have people from other ethnic groups as neighbors.[15] The effect size is identical to that in model 1, which further highlights the close association between ethnicity and religion in Nigeria.

[15] Table A4 in the appendix reports the marginal effects at the mean for model 4

In model 5, which was estimated using the Muslim subsample of respondents, violent conflict was statistically insignificant. The correlation between the error terms of the first- and second-stage regressions was also insignificant, which indicates that endogeneity was absent. I thus re-estimated the model using simple Oprobit regression. As shown in model 6, violent conflict remained statistically insignificant. This suggests that among Muslims, exposure to violent conflict has no statistically significant effect on hostility towards ethnic outgroup. When I treated all the variables as continuous and re-estimated all the models reported in Table 4 using 2SLS, the results remained consistent (See table A6 in the appendix).[16]

6.0. Conclusion

This study examined the effect of exposure to violent conflict on hostility towards ethno-religious outgroups among the Nigerian population and among its two major religious groups (Christians and Muslims). Causal identification stemmed from instrumenting conflict exposure with forest cover. The regression results showed that among the Nigerian population and among Christians, conflict exposure had a robust positive effect on outgroup hostility. A plausible explanation for this finding is that the threat of violent conflict fosters cohesion within ingroup members, erodes trust in outgroup members, and makes ingroup members less accommodating of outgroup members. This is especially so when the opposite party to the conflict constitutes a distinct cultural outgroup. Moreover, the main conflict affecting Christians involves nomadic Fulani pastoralists, who are Muslims. Among Muslims, violent conflict had a weak positive effect on outgroup hostility that was robust to neither a different operationalization of outgroup hostility nor an alternative estimation method. This could be because the main conflict affecting Muslims – i.e., the *Boko Haram* insurgency – does not involve

[16] Although I have used a buffer size of 30km while measuring exposure to violent conflict, forest cover, and the other relevant variables throughout this study, all the results reported are robust to alternative buffer sizes with radii of 20km and 50km. I have not provided these results in the paper, but would provide them upon request.

Christians. A significant number of Muslims are also affected by conflicts involving nomadic Fulani pastoralists.

The results also showed that religion is closely associated with ethnicity in Nigeria, and the population tends to conflate the two. This overlap makes intergroup boundaries salient and heightens the risk of conflict. If the Nigerian government intends to reduce violent conflict and outgroup hostility, it would have to adopt a policy that tackles these two factors simultaneously because each one reinforces the other. For instance, the government could reduce the incidence of violence by equipping its security agencies with the requisite skills and equipment needed to respond promptly and effectively to conflict situations, while simultaneously pursuing policies that foster social cohesion and elevate a shared national identity over ethnic and religious identities, e.g., by encouraging inter-ethnic and inter-religious dialogue. However, the latter recommendation might be difficult to achieve because it is not uncommon for Nigerian elites to exploit the ethnic and religious divisions among the population for political gain.

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Appendix

Table A1: Marginal effects at the mean for model 2 in Table 4

Outgroup hostility (Religion)$^{\phi}$	**Strongly like (1)**	**Somewhat like (2)**	**Wouldn't care (3)**	**Somewhat dislike (4)**	**Strongly dislike (5)**
Violent conflict$^{\#}$	-0.002***	-0.001	0.00	0.001**	0.002
	(0.001)	(0.001)	(0.00)	(0.00)	(0.002)
Nighttime light$^{\#}$	0.011**	0.004	-0.002	-0.004**	-0.009**
	(0.005)	(0.002)	(0.003)	(0.001)	(0.005)
Prevalence of stunting$^{\#}$	-0.143	-0.047	0.024	0.047	0.119
	(0.134)	(0.044)	(0.048)	(0.043)	(0.104)
Log Population size$^{\#}$	-0.032*	-0.01	0.005	0.01*	0.027*
	(0.017)	(0.008)	(0.009)	(0.005)	(0.015)
Educational level	0.019***	0.006*	-0.003	-0.006***	-0.016**
	(0.007)	(0.004)	(0.005)	(0.002)	(0.006)
Religious affiliation	-0.008	-0.003	0.001	0.003	0.007
	(0.03)	(0.01)	(0.005)	(0.01)	(0.025)
Gender	0.053**	0.017	-0.009	-0.017**	-0.044**
	(0.022)	(0.011)	(0.015)	(0.007)	(0.021)
Age	0.001	0.00	-0.00	-0.00	-0.001
	(0.001)	(0.00)	(0.00)	(0.00)	(0.001)

Note: *ϕ is the dependent variable, # denotes variables measured using buffers with a radius of 30km, standard errors are in parenthesis, *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Numbers in parenthesis below the response categories are the ordinal values assigned to them.*

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Table A2: Marginal effects at the mean for model 4 in Table 4

Outgroup hostility (religion)$^{\phi}$	**Strongly like (1)**	**Somewhat like (2)**	**Wouldn't care (3)**	**Somewhat dislike (4)**	**Strongly dislike (5)**
Violent conflict#	-0.002***	-0.00	0.001***	0.001**	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.001)
Nighttime light#	0.011**	0.003	-0.004**	-0.004**	-0.005**
	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
Prevalence of stunting#	-0.075	-0.018	0.027	0.028	0.038
	(0.133)	(0.033)	(0.05)	(0.049)	(0.067)
Log Population size#	-0.043**	-0.01	0.015**	0.016**	0.022*
	(0.017)	(0.008)	(0.008)	(0.007)	(0.011)
Educational level	0.023***	0.006*	-0.008**	-0.009***	-0.012***
	(0.006)	(0.003)	(0.003)	(0.002)	(0.004)
Religious affiliation	-0.029	-0.007	0.011	0.011	0.015
	(0.032)	(0.009)	(0.012)	(0.012)	(0.017)
Gender	0.034*	0.008	-0.012	-0.013*	-0.017
	(0.02)	(0.006)	(0.008)	(0.007)	(0.011)
Age	-0.00	-0.00	0.00	0.00	0.00
	(0.001)	(0.00)	(0.00)	(0.00)	(0.00)

Note: *ϕ is the dependent variable, # denotes variables measured using buffers with a radius of 30km, standard errors are in parenthesis, *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Numbers in parenthesis below the response categories are the ordinal values assigned to them.*

Table A3: Marginal effects at the mean for model 1 in Table 5

Outgroup hostility (Religion)$^{\phi}$	**Strongly like (1)**	**Somewhat like (2)**	**Wouldn't care (3)**	**Somewhat dislike (4)**	**Strongly dislike (5)**
Violent conflict#	-0.003***	-0.00	0.001	0.001**	0.001
	(0.001)	(0.00)	(0.001)	(0.00)	(0.001)
Nighttime light#	0.034***	0.00	-0.013	-0.01**	-0.011
	(0.013)	(0.015)	(0.01)	(0.005)	(0.014)
Prevalence of stunting#	0.465	0.006	-0.175	-0.142	-0.155
	(0.341)	(0.202)	(0.178)	(0.11)	(0.208)
Log Population size#	-0.094**	-0.001	0.035	0.029*	0.031
	(0.044)	(0.041)	(0.03)	(0.015)	(0.038)
Educational level	-0.00	-0.00	0.00	0.00	0.00
	(0.01)	(0.00)	(0.003)	(0.003)	(0.003)
Gender	-0.004	-0.00	0.001	0.001	0.001
	(0.031)	(0.002)	(0.012)	(0.009)	(0.01)
Age	0.001	0.00	-0.00	-0.00	-0.00
	(0.001)	(0.001)	(0.00)	(0.00)	(0.001)

Note: *ϕ is the dependent variable, # denotes variables measured using buffers with a radius of 30km, standard errors are in parenthesis, *** p<0.01, ** p<0.05, * p<0.10. Numbers in parenthesis below the response categories are the ordinal values assigned to them.*

Table A4: Marginal effects at the mean for model 4 in Table 5

Outgroup hostility (Ethnicity)$^{\phi}$	**Strongly like (1)**	**Somewhat like (2)**	**Wouldn't care (3)**	**Somewhat dislike (4)**	**Strongly dislike (5)**
Violent conflict$^{\#}$	-0.003**	0.00	0.001*	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.00)	(0.001)
Nighttime light$^{\#}$	0.023**	-0.001	-0.01	-0.006	-0.006
	(0.011)	(0.011)	(0.007)	(0.004)	(0.008)
Prevalence of stunting$^{\#}$	0.012	-0.00	-0.005	-0.003	-0.003
	(0.327)	(0.009)	(0.147)	(0.091)	(0.082)
Log Population size$^{\#}$	-0.103**	0.002	0.046*	0.029	0.026
	(0.044)	(0.05)	(0.028)	(0.019)	(0.035)
Educational level	0.018	-0.00	-0.008	-0.005	-0.004
	(0.011)	(0.009)	(0.006)	(0.004)	(0.006)
Gender	-0.038	0.001	0.017	0.01	0.009
	(0.032)	(0.018)	(0.016)	(0.01)	(0.015)
Age	0.001	-0.00	-0.00	-0.00	-0.00
	(0.001)	(0.00)	(0.001)	(0.00)	(0.00)

Note: *ϕ is the dependent variable, # denotes variables measured using buffers with a radius of 30km, standard errors are in parenthesis, *** p<0.01, ** p<0.05, * p<0.10. Numbers in parenthesis below the response categories are the ordinal values assigned to them.*

Table A5: Ethnic distribution of respondents

Ethnic group	Frequency (n)	Percent
Hausa	322	22.24
Igbo	251	17.33
Yoruba	328	22.65
Fulani	49	3.38
Ibibio	35	2.42
Kanuri	35	2.42
Ijaw	33	2.28
Tiv	26	1.80
Ikwere	25	1.73
Efik	24	1.66
Ebira	20	1.38
Idoma	19	1.31
Nupe	18	1.24
Igala	16	1.10
Isoko	10	0.69
Edo	10	0.69
Gwari	9	0.62
Kalabari	9	0.62
Jukun	7	0.48
Urhobo	4	0.28
Birom	3	0.21
Shuwa-Arab	1	0.07
Others	194	13.41
Total	**1,448**	**100.00**

Note: *Based on the Round 7 Afrobarometer survey data collected in 2017.*

Table A6: Replicating the results in Table 4 using two-stage least squares regression (2SLS)

Outgroup hostility$^{\phi}$	**Religion**		**Ethnicity**	
	(1)	**(2)**	**(3)**	**(4)**
Violent conflict#	0.002**	0.014***	0.002**	0.012***
	(0.001)	(0.004)	(0.001)	(0.004)
Nighttime light#		-0.239***		-0.198***
		(0.066)		(0.06)
Prevalence of stunting#		2.126***		1.529**
		(0.69)		(0.623)
Log Population size#		-0.005		-0.015
		(0.075)		(0.068)
Educational level		-0.097***		-0.094***
		(0.021)		(0.019)
Religious affiliation		0.176		0.231*
		(0.132)		(0.12)
Gender		-0.222***		-0.12*
		(0.073)		(0.066)
Age		-0.006**		-0.003
		(0.003)		(0.003)
Constant	2.552***	2.017**	2.286***	2.06**
	(0.072)	(0.96)	(0.065)	(0.868)
Estimation method	2SLS	2SLS	2SLS	2SLS
Ethnic group fixed effects	Yes	Yes	Yes	Yes
Observations	1439	1415	1438	1414
R-squared	0.116		0.118	
Durbin statistic	9.083***	12.284***	6.578**	10.475***
Wu-Hausman statistic	8.95***	12.068***	6.47**	10.277***
Sargan statistic	0.317	0.129	0.018	0.063
Basmann statistic	0.311	0.126	0.018	0.061

Note: *ϕ is the dependent variable, standard errors are in parenthesis, *** $p<0.01$, ** $p<0.05$, * $p<0.10$. # denotes variables measured using buffers with a radius of 30km. All models are estimated using two-stage least squares regression (2SLS).*

Table A7: Replicating the results in Table 5 using two-stage least squares regression (2SLS)

Outgroup hostility$^{\phi}$	**Religion**			**Ethnicity**		
	(1) (Xtian)	**(2) (Muslim)**	**(3) (Muslim)**	**(4) (Xtian)**	**(5) (Muslim)**	**(6) (Muslim)**
Violent conflict$^{\#}$	0.025***	0.004	0.001	0.021***	0.004	0.001
	(0.007)	(0.005)	(0.001)	(0.006)	(0.005)	(0.001)
Nighttime light$^{\#}$	-0.464***	-0.056	-0.021	-0.398***	-0.053	-0.017
	(0.113)	(0.068)	(0.022)	(0.105)	(0.061)	(0.02)
Prevalence of stunting$^{\#}$	-2.165**	2.614*	1.953***	-0.916	1.696	1.018*
	(1.041)	(1.362)	(0.619)	(0.975)	(1.231)	(0.558)
Log Population size$^{\#}$	0.112	-0.045	0.019	0.121	-0.048	0.018
	(0.115)	(0.142)	(0.079)	(0.108)	(0.128)	(0.071)
Educational level	0.019	-0.111***	-0.103***	-0.023	-0.091***	-0.083***
	(0.031)	(0.029)	(0.025)	(0.029)	(0.026)	(0.022)
Gender	-0.019	-0.52***	-0.523***	0.065	-0.381***	-0.384***
	(0.097)	(0.101)	(0.102)	(0.09)	(0.091)	(0.092)
Age	-0.005	-0.005	-0.004	-0.003	0.00	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	1.24	2.54*	1.994*	1.045	2.49*	1.93**
	(1.847)	(1.43)	(1.026)	(1.729)	(1.292)	(.924)
Estimation method	2SLS	2SLS	OLS	2SLS	2SLS	OLS
Ethnic group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	807	608	608	806	608	608
$\mathbf{R^2}$		0.178	0.192		0.114	0.135
Durbin statistic	14.998***	0.301		13.738***	0.39	
Wu-Hausman statistic	14.657***	0.29		13.404***	0.376	
Sargan statistic	1.24	5.154**		1.61	1.411	
Basmann statistic	1.191	5.01**		1.547	1.363	

Note: *ϕ is the dependent variable, standard errors are in parenthesis, *** $p<0.01$, ** $p<0.05$, * $p<0.10$. # denotes variables measured using buffers with a radius of 30km. All models are estimated using two-stage least squares regression (2SLS) except for models 3 and 6 which are estimated using ordinary least squares (OLS) regression.*