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Inverted "U" of fear: The paradox of conflict exposure and expected victimization in Kaduna, Nigeria

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Abstract
Using novel survey data collected from the Northern Nigerian state of Kaduna, this study examines the effect of exposure to violent conflict on people's expectation of being directly affected by violent conflict in the future. The regression results show that there is a curvilinear relationship akin to an inverted "U" between conflict exposure and expected victimization. This suggests that at low levels of conflict exposure, people worry that they will be victimized. As conflict exposure increases, so does their fear of being victimized. This persists until the point at which expected victimization peaks. Further exposure to violent conflict beyond this peak leads to a decline in expected victimization. The decline after the peak might be because the threat of violent conflict prompts people to rely more heavily on their ethnoreligious kinship ties for both material and nonmaterial support, which in turn attenuates their fear of being victimized.

Keywords
Violent conflict, Victimization, Social cohesion, Religion, Ethnicity, Kaduna, Nigeria

JEL Classification
D74, N37

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1. Introduction

In the 2024 Global Terrorism Index (GTI), Nigeria was one of the countries most affected by terrorism. It ranked eighth in the world and fourth in Africa (Institute for Economics and Peace 2024). Data from the Armed Conflict Location and Events Database (ACLED) (Raleigh et al. 2010) shows that in 2023 alone, Nigeria recorded a total of 3,265 violent conflict incidents, making it the country's second most violent year since 1997.[2] The Round 8 Afrobarometer survey (BenYishay et al. 2017), which is representative of Nigeria's population, shows that in 2020, 18 percent of Nigerians had experienced some form of violence in their neighborhood during the past two years. The Round 9 Afrobarometer survey, conducted in 2022, shows that 76 percent of Nigerians think the country is unsafe to live in; 71 percent think the country has become less safe to live in compared to five years ago; and 73 percent think the government has performed poorly in preventing and resolving conflicts across the country.

Yet, although there is considerable violence in Nigeria, its incidence is unevenly spread across Nigeria's 36 states, with a few of them accounting for most of the incidents. This study focuses on the Northern Nigerian state of Kaduna, which has the second highest incidence of violent conflict in the country. Kaduna has featured frequently in both the domestic and international news lately—sadly, not for good reasons. On March 7, 2024, armed men stormed a school and kidnapped over 287 pupils along with some teachers (Ewokor & Rhoden-Paul 2024; Voice of America 2024). On December 3, 2023, a drone strike launched by the Nigerian army killed over 80 people at a religious celebration; they had been mistaken for bandits operating in the vicinity (Sunday 2023; Punch Newspaper 2023). Besides the nagging problem of banditry and ransom-driven abductions, the state is also grappling with intercommunal violence between nomadic herders and sedentary communities (Voice of America 2023; Tuki 2023).

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[2] I define violent conflicts as incidents that fall under any of the following three categories: Violence against civilians, Battles, and Explosions/Remote violence.

Relying on novel survey data collected from the state of Kaduna as part of the Transnational Perspectives on Migration and Integration (TRANSMIT) research project, this study seeks to examine the effect of exposure to violent conflict on expected victimization among the state's population.[3] More specifically, this study empirically tests whether there is a curvilinear relationship akin to an inverted "U" between conflict exposure and expected victimization. To the best of my knowledge, a similar study has not been conducted in Nigeria.

The decision to check for a curvilinear relationship was driven by the high incidence of violent conflict in Kaduna. The ACLED dataset (Raleigh et al. 2010) shows that between 2018 to 2023, there were 1,403 violent conflict incidents in the state, 69 percent of which caused at least one fatality. Eight percent of these incidents were categorized as Explosions/Remote violence, 29 percent were categorized as Battles, while the remaining 63 percent were categorized as Violence against civilians. Kaduna has a long history of violent conflicts dating back to the 1980s (Scacco & Warren 2021; Angerbrandt 2018, 2011; Suberu 2013). The state's residents were likely very worried about being victimized at the onset of the conflict. However, with its frequent occurrence, coupled with the inability of Nigeria's security agencies to effectively address the nagging problem of insecurity, the population might have developed coping strategies that enable them to carry on with their "normal" lives despite the conflict, which in turn lowers their expected victimization.

The descriptive results show that 65 percent of the population in Kaduna think they are either "somewhat unlikely" or "very unlikely" to be victims of violent conflict in one year's time. Only 23 percent of them think they are "somewhat likely" or "very likely" to be victimized; the remaining 12 percent of the population think the likelihood of them being victimized in one year's time is the same as that at the point of the survey (i.e., 2021). The low expectation of being victimized among the population in Kaduna is particularly striking given the high conflict incidence in the state. The regression results show that there is indeed a curvilinear relationship between conflict exposure and expected victimization. This suggests that at the initial stages of conflict

[3] For more information on the TRANSMIT project visit: https://www.projekte.hu-berlin.de/en/transmit

exposure, people fear that they will be victimized. As conflict exposure increases, so does expected victimization. This persists until expected victimization peaks. At this point, people are most worried about being victimized. Further exposure to violent conflict beyond this peak leads to a decline in expected victimization. A plausible reason for the decline in expected victimization after the peak, which I am able to show with the data, is that exposure to violent conflict strengthens cohesion within ethnoreligious groups. Put differently, the fear of being victimized makes people rely more heavily on their ethnoreligious kinship ties, which in turn enables them to deal with the existential threat posed by violent conflict.

Even though reliance upon ethnoreligious kinship ties could engender resilience among people exposed to violent conflict, it could also be problematic because increased cohesion within ethnoreligious groups makes intergroup boundaries salient. This could in turn heighten the risk of intergroup conflict—a phenomenon that Schuab (2014) refers to as "solidarity with a sharp edge." This is especially relevant in the case of Kaduna, where violent conflicts and reprisals sometimes occur along ethnoreligious lines (e.g., Tuki 2023; Scacco & Warren 2021; Suberu 2013).

This rest of this study is organized as follows: Section 2 discusses some relevant theories and states the hypotheses. Section 3 introduces the data, operationalizes the variables that will be used to estimate the regression models, and specifies the general form of regression model. Section 4 presents the regression results and discusses them, while Section 5 summarizes the study and concludes.

2. Theoretical considerations

Terror management theory "posits that people are consistently, and unconsciously, motivated to maintain faith in their cultural worldviews, self-esteem, and close relationships to protect themselves from the anxiety produced by awareness that death is inescapable." (Darrell & Pyszczynski 2016, p. 6). Put differently, cultural world views, self-esteem, and close interpersonal relationships serve as anxiety buffers that enable people to carry on with their normal lives despite being aware of death's inevitability. These buffers are crucial because unrestrained anxiety could lead to paralyzing fears that "undermine the goal-directed behavior necessary for our survival." (Park & Pyszczynski 2016, p. 194). Darrell and Pyszczynski (2016, p. 4) defined cultural world views as "symbolic constructions that are by definition abstractions of observable reality, and therefore cannot be directly observed." This means cultural world views are akin to a lens through which people view and make sense of the uncertain world around them. Because cultural world views may not be underpinned by objective reality, they need to be constantly validated by people who also share the same beliefs: "Just as faith in our personal value depends on others sharing our positive self-evaluations, so too does faith in our conception of external reality depend on others sharing these conceptions." (Pyszczynski et al. 1997, p. 16). In a similar vein, people with low self-esteem and those who do not have close relationships upon which they could rely usually find it difficult to deal with anxieties induced by mortality salience (Lancaster et al. 2016).

Awareness of one's mortality—i.e., mortality salience—has been found to foster cohesion among ingroup members and prejudice towards outgroup members. This is because having ingroup members who share the same cultural worldviews reinforces people's belief in that worldview and attenuates their existential anxieties. Conversely, outgroup members who have different cultural worldviews challenge the cultural worldviews of ingroup members, hence putting pressure on their anxiety buffer (Harmon-Jones et al. 1996). These intergroup distinctions could be based on religion, ethnicity, nationality and political orientation (Pyszczynski et al. 1997). Castano et al. (2002) have highlighted the importance of integrating terror management theory (TMT) with the theory of intergroup relations, as this offers an enhanced understanding of human behavior: "Insights from TMT theory might in fact be used to understand what are the fundamental fears and needs of the individual/group member, whereas research on intergroup relations tells us about the specific mechanisms." (Castano et al. 2002 p. 137). Moreover, they note that if mortality salience indeed fosters positive attitudes toward ingroup members, then individuals must perceive the ingroup as "having a real existence, as being a real entity"—a phenomenon referred to as entitativity (Castano et al. 2002, p. 136; Lickel et al. 2006).

Some empirical studies have shown that mortality salience indeed strengthens ingroup cohesion and leads to outgroup prejudice. In an experimental study, Greenberg et al. (1990) found that mortality salience prompted Christians to view their co-religionists more favorably than Jews. Moreover, Christians who had been primed by being reminded about death viewed Jews more unfavorably than the control group that had not been primed. In a study conducted among university students in Italy, Castano et al. (2002) found that the treatment group that had been reminded about death (compared to the control condition) assessed their fellow Italians more favorably than Germans, identified more with their ingroup members, and perceived the ingroup as being more entitative. Bradley et al. (2012) conducted a study among white students in the United States in which they found that respondents who had been reminded about their mortality took longer to associate names typically borne by black people with positive attributes compared to participants in the treatment condition. In a recent study, Garshasbi and Maleh (2024) have shown that children residing in Al-Hawl refugee camp in northeastern Syria are particularly vulnerable to Islamist radicalization. This is because they face discrimination from other children at school and have difficulty associating with children residing outside the camp—due to the tendency for the camp's residents to be associated with ISIS. Moreover, the high rate of mortality in the camp due to violence and the absence of basic necessities makes death salient among the camp's residents. These children, in a bid to attenuate their death-related anxieties, might resort to embracing ISIS ideology as a means to develop self-esteem and a sense of purpose.

In a study conducted in the wake of a terrorist attack perpetrated by the radical Islamist group *Boko Haram,* Harding and Nwokolo (2023) found that exposure to violence weakened Nigerians' sense of national identity and strengthened their feeling of ethnic belonging. Analyzing survey data for Nigeria, Tuki (2024) found that exposure to violent conflict made Nigerians reluctant to have people of a different ethnicity and religion as neighbors. He argued that this was because the threat posed by violent conflict fostered ingroup cohesion and eroded trust in outgroup members. This was especially so when the opposite party to the conflict constituted a distinct cultural outgroup. In their study, which examined the effect of the Nepalese civil war on social cohesion, Gilligan et al. (2014) found that exposure to violent conflict had a positive effect on social cohesion. They explained their findings using the "purging" and "coping" mechanisms. The *purging* mechanism functioned such that people who had weak social networks fled the communities due to conflict, leaving behind those with strong social networks. The *coping* mechanism functioned such that those who remained in the communities despite the conflict (i.e., those with strong social networks) pooled their resources so they could better cope with the existential threat confronting them.

Returning to the case of Kaduna, exposure to violent conflict can be viewed as an existential threat that engenders mortality salience. Mortality salience in turn, fosters ingroup cohesion by prompting people to attach more importance to their ethnoreligious identities. The residents at Kaduna, like most Nigerians, have a high level of religiosity. The TRANSMIT survey dataset upon which this study relies shows that all respondents (n = 1,353) had a religious affiliation, with Muslims and Christians represented in the ratio 56:44. The survey had a question that asked respondents to choose which aspect of their identity (i.e., ethnicity, religion, or nationality) was most important to them: 74 percent of them chose their religion, 5 percent chose their ethnicity, 4 percent chose their nationality, while the remaining 16 percent said all identities were equally important. The survey also showed that 95 percent of the respondents agreed that the rules of the Bible/Quran were more important to them than the laws of Nigeria. Given this background, I expect that being exposed to violent conflict would have a curvilinear effect on people's expectation that they would be victimized in the future. This relationship, which is akin to an inverted "U", implies that at the initial stages of conflict exposure, people worry that they will be victimized. As conflict exposure increases, so does their fear of being victimized. This persists until the point at which expected victimization peaks. At this point, people are most afraid of being victimized. Further exposure to violent conflict beyond this peak leads to decline in expected victimization.

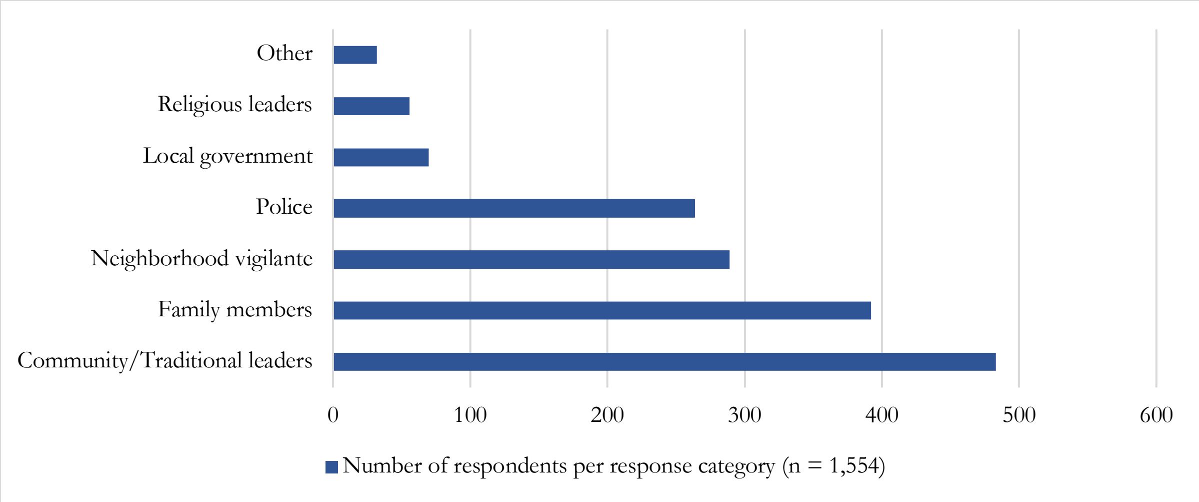

Figure 1: Nigerians' first call when in need of security-related assistance

Note: The y-axis shows the institutions that Nigerians first call upon when in need of security-related assistance. The x-axis shows the number of respondents associated with the various institutions. The figure is based on the following question in the Round 8 Afrobarometer survey conducted in 2020: "To whom do you normally go to first for assistance when you are concerned about your security and the security of your family?"

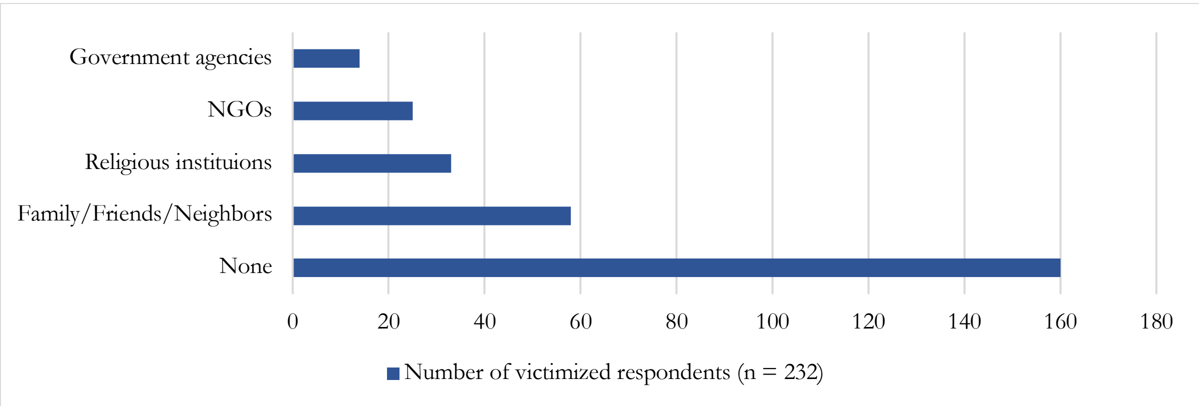

Figure 2: Source of assistance among people who have been victimized in Kaduna

Note: The y-axis shows the source of assistance received by the 232 respondents in Kaduna who reported that they had been directly affected by violence during the past decade (i.e., 2011–2021). The x-axis shows the number of respondents associated with the response categories. Respondents were allowed to select multiple sources of assistance. The figure is based on the Transnational Perspectives on Migration and Integration (TRANSMIT) survey conducted in Kaduna in 2021.

One reason for the decline in expected victimization after the peak could be that conflict-induced anxieties prompt people to rely upon their ethnoreligious networks for both material and non-material support. These networks serve as buffers that enable people to carry on with their "normal" lives despite the threat of violence. People might prefer to rely upon their ethnoreligious networks than security agencies in times of crises because they have more trust in traditional institutions than formal institutions. Security agencies are sometimes slow in responding to conflict

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situations, and there have been reports of security personnel siding with their co-ethnics and co-religionists during conflicts (Human Rights Watch 2024; Krause 2011).[4] Data obtained from the Round 9 Afrobarometer survey (BenYishay et al. 2017) conducted in 2022 supports this pattern: 52 percent of Nigerians do not trust the police at all; 46 percent do not trust the president at all; 43 percent do not trust the local government authorities at all. However, the level of distrust in religious and traditional authorities is much lower: Only 20 percent of the population do not trust traditional rulers at all; the estimate for religious leaders is 16 percent. As shown in Figure 1, the police are not the first port of call when Nigerians need security-related assistance; they tend to rely more heavily on traditional rulers, family members, and neighborhood vigilante groups. As shown in Figure 2, most people who have been directly affected by violence in Kaduna did not receive any support. Among those who did, the main sources of support were family and friends/neighbors, religious institutions, and non-governmental organizations (NGO's); the government played a limited role. Recognizing the rising threat of insecurity across Nigeria, many communities have established vigilante groups, with some of them committed to protecting specific ethnic and religious groups (International Crisis Group 2022; Charles 2021; Chukwuma 2017; Higazi 2007).

A point worth highlighting is that the state of Kaduna has a long history of ethnoreligious violence; this has led to residential segregation along the lines of ethnicity and religion (Scacco & Warren 2021; Hoffmann 2017; Suberu 2013). Segregation makes it easier for communities to establish vigilante groups. This is because the common ethnicity and religion among community members enables them to overcome the problems associated with collective action more easily. Put differently, people who belong to the same ethnic and religious groups find it easier to cooperate in attaining the shared goal of providing security for their community. The discussion so far leads to the following hypotheses that this study seeks to test:

[4] The TRANSMIT dataset shows that one in six households had experienced some form of violence during the past decade (i.e., 2011–2021).

H1: *Among the population in Kaduna there is a curvilinear relationship between exposure to violent conflict and expected victimization.*

H2: *Among the population in Kaduna, exposure to violent conflict positively correlates with the importance that people attach to their ethnoreligious identities.*

3. Data and methodology

This study relies on the Transnational Perspectives on Migration and Integration (TRANSMIT) survey data collected from the Northern Nigerian state of Kaduna in 2021.[5] A total of 1,353 respondents aged 15 and above were interviewed. The data were collected using clustered random sampling. Data were collected from all 23 local government areas (LGAs) (i.e., municipalities) in the state except for four of them (i.e., Giwa, Birnin Gwari, Kauru, and Zangon Kataf). These four LGAs were excluded from the sampling frame because of the high risk of intercommunal conflicts and banditry there, which made them unsafe for enumerators to conduct interviews in. Section B in the appendix discusses the sampling strategy in more detail. Section 3.1 discusses the variables that will be used to estimate the regression models, while Table A1 in the appendix reports the summary statistics for these variables.

3.1. Operationalization of the variables

3.1.1. Dependent variable

Expected victimization. This variable measure's the respondents' expectations that they would be victims of violent conflict within a year. It was derived from the question, "Looking towards the future, say one year from now, how likely is it that you will be affected by violence?" The responses were measured on a scale with five ordinal categories ranging from "0 = very unlikely" to "4 = very likely."

[5] See note 3 above

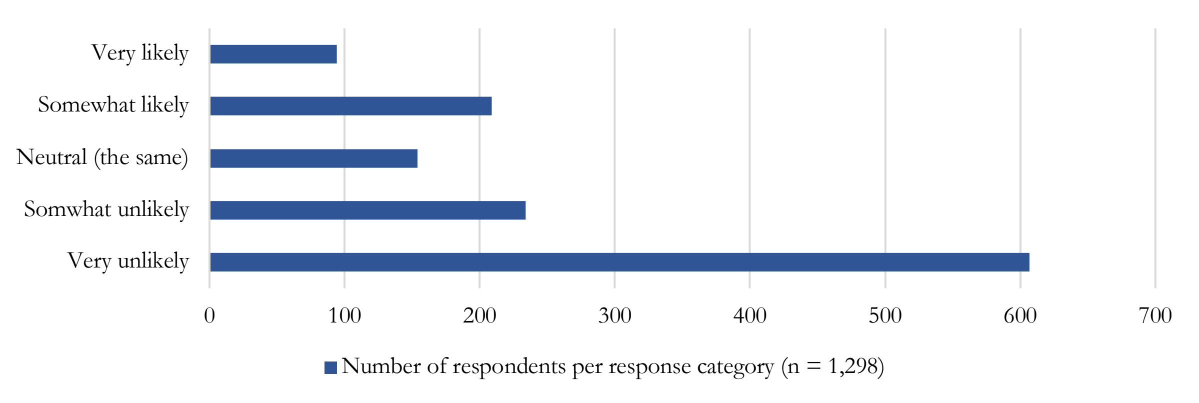

Figure 3: Expected victimization among the population in Kaduna

Note: The vertical axis shows the various response categories to the question asking respondents about their expectation that they would be affected by violent conflict within a year. The values on the horizontal axis show the number of respondents associated with the various response categories.

As shown in Figure 3, most respondents do not think they will be affected by violence within a year. 65 percent of them chose either the "very unlikely" or "somewhat unlikely" response categories. Only 23 percent of them think they are either "very likely" or "somewhat likely" to be affected by violence. I developed a binary version of the dependent variable in which I coded the "very likely" and "somewhat likely" response categories as 1 and the remaining three response categories as 0. I used this variable to conduct a robustness check.

3.1.2. Explanatory variable

Conflict. This measures the total number of violent conflict incidents that occurred within the 10km buffer around the respondents' geolocations from 1997 to 2020.[6] Using QGIS software, I developed this variable by leveraging the georeferenced dimension of the TRANSMIT survey data and the Armed Conflict Location and Events Dataset (ACLED) (Raleigh et al. 2010). Based on the ACLED dataset, I define violent conflicts as events belong to one of these three categories: Battles, Violence against civilians, and Explosions/Remote violence. I considered the conflict incidents within the buffer from 1997 to 2020 because I am particularly interested in the long-term effect of conflict exposure. Some studies have shown that effect of violent conflict tends to persist and

[6] I used the start year of 1997 because the ACLED data is available beginning from then. I excluded conflict incidents that occurred after 2020 to lag the explanatory variable. This mitigates the potential problem of reverse causation since the dependent variable—i.e., expected victimization—is measured in 2021.

shapes behavior in the present (e.g., Tuki 2024a; Wagoner & Brescó 2016; Tint 2010). 79 percent of the 1,353 respondents had at least one conflict incident within the 10km buffer around their dwellings. 42 percent of them had at least 10 incidents within the buffer.

Because I am particularly interested in checking whether exposure to violent conflict has a curvilinear effect on expect victimization, I developed the main explanatory variable—i.e., *conflict square*—by taking the square of the total number of conflicts within the 10km buffer. Because 29 percent of the respondents had no conflict incident within the 10km buffer, I dealt with the zeroes by adding a value of 1 to the cumulative number of conflicts within the respective buffers before taking the square. Finally, I took the log of the value derived. See equation 1 below:

$$conflict\ square_{1997-2020} = log[(conflict_{1997-2020} + 1)^2] \tag{1}$$

3.1.3. Control variables

I considered control variables for past victimization, perceived state capacity, perception of gun proliferation in the community, socioeconomic condition, and the demographic attributes of the respondents. I discuss each of these variables below:

Past victimization. This is a dummy variable that takes the value of 1 if the respondent or a close family member had been directly affected by violence during the past decade (i.e., 2010–2021) and 0 otherwise. It was derived from the question, "During the last 10 years, have you or your close family members been affected by violence? By 'affected' I mean (a) You or your close family were threatened by violence. (b) You or one of your close family members was injured or killed, or (c) Your home or property was destroyed by an attacker." 18 percent of the respondents had been victimized, which translates into one in six households. Victimization differs from conflict exposure (i.e., the explanatory variable) because it measures the concrete experience of violence. Conversely, being exposed to violent conflict does not necessarily imply being victimized. This is because it is possible for people to live in conflict zones and devise coping strategies that enable them to carry on with their "normal" lives despite the conflict.

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State capacity. This measures the degree to which respondents think the police are effectively playing their role of providing security. It was derived from the question, "To what extent do you agree with the following statement: The police are doing a good job of providing security for the community?" The responses were measured on a scale with five ordinal categories ranging from "0 = strongly disagree" to "4 = strongly agree." I included this variable in the model because it could confound the relationship between the dependent and explanatory variables. For instance, people who think the police are ineffective might feel unsafe, and hence expect to be victimized. On the other hand, people who think the police are ineffective might be more inclined to resolve disputes by taking the law into their own hands, which in turn could increase the risk of violent conflict (Bagu & Smith 2017). 64 percent of the population in Kaduna either "strongly agree" or "somewhat agree" that the police are doing a good job at providing security. 31 percent of them either "somewhat disagree" or "strongly disagree" with the statement.

Gun proliferation. This measures the respondents' perceptions of the trend in gun ownership in their communities. It was derived from the question, "Has the ownership of guns become more common, less common or stayed about the same in the last 10 years?" The responses were measured on a scale with the following three ordinal categories, "0 = less common," "1 = stayed the same," "2 = more common." I included this variable into the model because the perception of weapon proliferation could also confound the relationship between the dependent and explanatory variables. When people feel that gun ownership is rising (e.g., in neighboring rival communities), this could heighten their level of perceived threat and expected victimization (Eke 2022, 2022a). To attenuate the threat, other communities might resort to purchasing firearms. This could increase the risk of violence because people who possess firearms might use them when they feel threatened (Schaub 2014). This mechanism is especially plausible in scenarios where the population is polarized along ethnoreligious lines and intergroup boundaries are salient. 49 percent of the population in Kaduna think gun ownership has become more common in their communities during the past decade, 12 percent think gun ownership has stayed the same, while the remaining 39 percent think gun ownership has become less common.

Household income. This measures the socioeconomic circumstance of the households in which respondents reside. It was derived from the question, "Which of the following statements best describe the current economic situation of your household?" The responses were measured on a scale with five ordinal categories ranging from, "0 = money is not enough for food" to "4 = we can afford to buy almost anything." Socioeconomic condition could also potentially confound the relationship between violent conflict and expected victimization. For instance, deprivation could increase the risk of conflict by lowering the opportunity cost of joining a rebel group (Collier 2008; Collier & Hoeffler 2004). On the other hand, wealthy households and wealthy communities might have sufficient resources to finance private security and vigilante groups to address the problem of insecurity, which in turn could lower their expected victimization. On the other hand, people who are wealthy might have a high level of expected victimization because their wealth might make them potential targets for criminal groups (Hinton & Montalvo 2016).

Demographic covariates. I considered control variables for the respondents' demographic attributes. This includes age, gender, and marital status. Gender takes the value of 1 if the respondent is female and 0 if male. Marital status takes the value of 1 if the respondent is married or has ever been married and 0 otherwise. Age is measured in years.

3.2. Analytical technique

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

$$\gamma_t = \beta_0 + \beta_1 conflict\ square_{1997-2020} + \beta_2 \lambda'_t + \mu_t \qquad (2)$$

Where γ_t is the dependent variable which measures expected victimization at time t when the survey was conducted (i.e., 2021), λ'_t is a vector of control variables measuring state capacity, gun proliferation, socioeconomic status, and the respondents' demographic attributes, β_0 is the intercept, β_1 and β_2 are the coefficients of the explanatory and control variables respectively, and

μ_t is the error term. Although I used ordinary least squares (OLS) regression as the main analytical technique, I conducted a robustness check in which I operationalized the dependent variable binarily and estimated the regression using linear probability model (LPM).

4. Results and discussion

4.1. Conflict and expected victimization

Table 1: OLS models regressing expected victimization on the square of conflict

Expected victimization†	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Conflict square	-0.025**	-0.033***	-0.037***	-0.01***		
	(0.01)	(0.01)	(0.011)	(0.003)		
Conflict square [UCDP]					-0.045***	
					(0.012)	
Conflict square [GTD]						-0.03**
						(0.013)
Past victimization		0.352***	0.36***	0.112***	0.346***	0.35***
		(0.103)	(0.103)	(0.033)	(0.103)	(0.103)
State capacity		-0.081***	-0.081***	-0.021***	-0.078***	-0.078***
		(0.025)	(0.025)	(0.008)	(0.025)	(0.025)
Gun proliferation		0.102**	0.103**	0.032***	0.101**	0.1**
		(0.04)	(0.041)	(0.013)	(0.041)	(0.041)
Household income			0.015	-0.005	0.016	0.013
			(0.041)	(0.013)	(0.041)	(0.041)
Age			0.002	0.00	0.002	0.002
			(0.003)	(0.001)	(0.003)	(0.003)
Gender			0.115	0.021	0.11	0.11
			(0.079)	(0.025)	(0.079)	(0.079)
Marital status			-0.152	-0.048	-0.145	-0.138
			(0.106)	(0.032)	(0.105)	(0.107)
Constant	1.293***	1.354***	1.339***	0.316***	1.296***	1.287***
	(0.06)	(0.106)	(0.166)	(0.049)	(0.16)	(0.166)
Estimation method	OLS	OLS	OLS	LPM	OLS	OLS
Observations	1298	1298	1298	1298	1298	1298
R-squared	0.004	0.029	0.032	0.028	0.033	.028
AIC statistic	4478.023	4450.346	4454.686	1430.696	4453.914	4460.734
BIC statistic	4488.361	4476.189	4501.203	1477.213	4500.431	4507.251

Note: Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1, † is the dependent variable, conflict is measured using buffers with a 10km radius. All models are estimated using ordinary least squares (OLS) regression except for model 4 which is estimated using linear probability model (LPM). The dependent variable is measured on a scale with five ordinal categories in all the models except for model 4 where it is measured binarily.

Table 1 reports the results of OLS models regressing expected victimization on the square of conflict. I added the variables into the model in a stepwise manner to mitigate the problem of multicollinearity. This also prevents a scenario whereby the results are dependent on the inclusion of a certain combination of variables in the model. In model 1 where I considered only the square of conflict, it carried the expected negative sign and was significant at the five percent level.[7] This supports Hypothesis 1 that the effect of violent conflict on expected victimization is curvilinear—i.e., akin to an inverted "U". Put differently, at the initial stages of conflict exposure, people worry that they will be victimized by violent conflict. As conflict exposure rises, so does expected victimization. This persists until a point is reached at which expected victimization peaks. At this point, people are most afraid that they would be victimized. Further exposure to violent conflict beyond the peak rather leads to a decline in expected victimization.

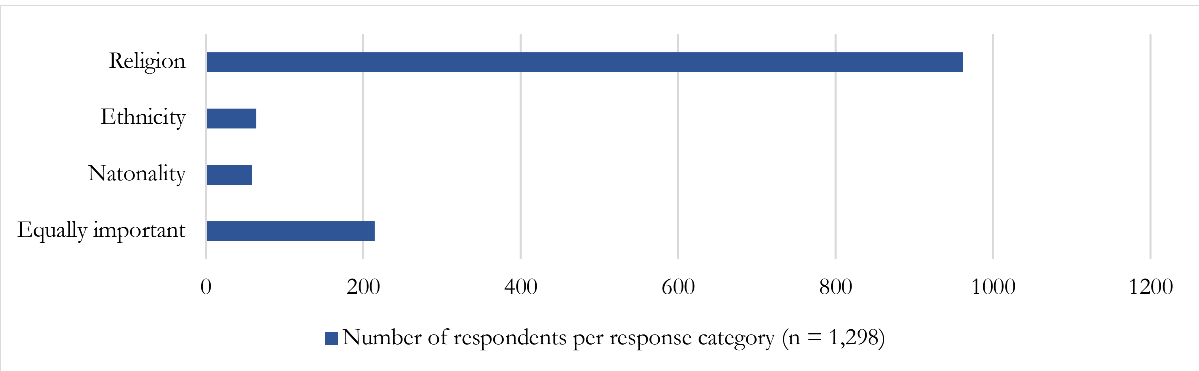
In model 2 where I controlled for past victimization, state capacity, and gun proliferation, the square of conflict retained its negative sign and its significance level increased to one percent. Past victimization was significant at the one percent level and carried a positive sign, which suggests that people who have been directly affected by violence (compared to those who have not) are likely to have a higher level of expected victimization. State capacity carried a negative sign and was significant at the one percent level. This suggests that people who think the police are doing a good job at providing security have a lower level of expected victimization. Gun proliferation carried a positive sign, which indicates that people who think gun ownership has increased are likely to have a high level of expected victimization. In model 3 where I controlled for the respondents' socioeconomic status and demographic attributes, the square of conflict retained its negative sign and remained significant. The statistical insignificance of household income implies that the poor do not differ from the rich in terms of the level of expected victimization. The statistical insignificance of gender, marital status, and age suggest that in terms of expected victimization, men do not differ from women; married people do not differ from their unmarried counterparts; and the old are do not differ from the young.

To check whether these results are affected by the way the dependent variable was operationalized and the estimation method employed, I estimated model 4 using linear probability

[7] As discussed in section 3.2.1, this variable is logged. I estimated some models in which I used the unlogged version of the square of conflict; the results were consistent with those reported in Table 1. I have not reported these results in the paper.

model (LPM) and a binary operationalization of expected victimization. The square of violent conflict remained significant at the one percent level and maintained its negative sign. To check whether the results were also influenced by the source of the conflict data, I developed alternative versions of the explanatory variable based on data obtained from the Uppsala Conflict Data Program (UCDP) (Sundberg & Melander 2013)[8] and the Global Terrorism Database (GTD) (National Consortium for the Study of Terrorism and Responses to Terrorism 2022).[9] The UCDP and GTD datasets differ from that obtained from ACLED in terms of the duration for which data are available and the inclusion criteria for events into the database. The UCDP dataset records only conflict incidents that caused at least one fatality. Because the UCDP dataset is available beginning from 1989, I considered all the conflict incidents within the 10km buffer from 1989 to 2020 while developing the measure of conflict exposure. The GTD dataset records terrorist activity around the world and, like the ACLED dataset, does not impose a fatality threshold as an inclusion criterion. Because the GTD dataset is available from 1970, I computed all the incidents within the buffer from 1970 to 2020. As shown in models 5 and 6 respectively, the conflict variables derived from UCDP and GTD both carried the expected negative sign and were statistically significant. Suffice it to add that the results reported in Table 1 are robust to an alternative operationalization of the explanatory variable where I measured conflict exposure with buffers that have a radius of 5km (see Table A2 in the appendix).

4.2. Conflict and cultural salience



[8] To access the UCDP's Georeferenced Events Dataset, visit: https://ucdp.uu.se/downloads/

[9] To access the GTD dataset, visit: https://www.start.umd.edu/gtd/

Figure 4: Most important aspect of identity among the population in Kaduna

Note: The vertical axis shows the various aspects of the respondents' identity, while the values on the horizontal axis show the total number of respondents who attach the most importance to the various identity categories.

To test the second hypothesis regarding whether exposure to violent conflict indeed fosters ingroup cohesion by prompting people to attach more importance to their ethnoreligious identity, I relied on a question in the TRANSMIT survey asking respondents which aspect of their identity was most important to them: "So far, we know your religion, ethnicity, and nationality. Among these three items, which is most important to you?" As shown in figure 4, people in Kaduna attach the most importance to their religious identity. 962 respondents, which is equivalent to 74 percent of the sample, chose their religious identity, 5 percent chose their ethnicity, 4 percent chose their nationality, while the remaining 16 percent said all identities were equally important. This shows that people in Kaduna have a weak sense of national identity. This pattern is not peculiar to Kaduna, but also applies to the larger Nigerian population (Agbiboa & Maiangwa 2013). An important point worth highlighting is that religion and ethnicity overlap to a great extent in Kaduna and Nigeria at large. This intersection is rooted in Nigeria's precolonial and colonial histories (Tuki 2024; Tuki 2023, p. 15). I thus developed a dummy variable—*Cultural salience*—which takes the value of 1 if respondents attached the most importance to either their ethnicity or religion, and 0 otherwise.

Table 2 reports the results of LPM models where I regressed cultural salience on exposure to violent conflict. The focus here is on the cumulative number of violent conflict incidents within the 10km buffer and not the logged square conflict (i.e. conflict square) as had been the case earlier. I operationalized the explanatory variable this way because I am particularly interested in the linear effect of conflict exposure on cultural salience. In model 1 where I considered only conflict, it carried the expected positive sign and was significant at the one percent level. This supports Hypothesis 2 which states that conflict exposure prompts people to attach more importance to their ethnoreligious identities. This might be because people draw upon the material and non-material resources within their ethnoreligious networks, which enables them to better cope with the existential threat posed by violent conflict. This is consistent with the observation of Castano et al. (2002, p. 141): "[T]he ingroup might serve as an anxiety buffer per se. Ingroup entitativity might be the foremost ingroup feature that group members will care about when they are confronted with the threat of annihilation of their personal self."

Table 2: LPM models regressing cultural salience on violent conflict

Cultural salience†	**(1)**	**(2)**	**(3)**	**(4)**
Conflict	0.001***	0.001***		
	(0.00)	(0.00)		
Conflict [UCDP]			0.002***	
			(0.001)	
Conflict [GTD]				0.001***
				(0.00)
Past victimization		-0.089***	-0.089***	-0.09***
		(0.032)	(0.032)	(0.032)
State capacity		-0.024***	-0.025***	-0.024***
		(0.007)	(0.007)	(0.007)
Gun proliferation		-0.001	0.00	0.00
		(0.012)	(0.012)	(0.012)
Constant	0.767***	0.845***	0.846***	0.848***
	(0.014)	(0.027)	(0.027)	(0.027)
Estimation method	LPM	LPM	LPM	LPM
Observations	1298	1298	1298	1298
R-squared	0.008	0.023	0.023	0.02
AIC statistic	1342.902	1329.484	1329.558	1333.258
BIC statistic	1353.239	1355.327	1355.401	1359.101

Note: Robust standard errors are in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, † is the dependent variable, violent conflict is measured using buffers with a 10km radius. All regressions are estimated using linear probability model (LPM). Cultural salience is a dummy variable that takes the value of 1 if respondents attach more importance to either their religion or ethnicity than their nationality.

In model 2 where I added control variables for past victimization, state capacity, and gun proliferation, conflict remained significant at the one percent level and maintained its positive sign. Among the control variables, past victimization and state capacity were significant. Past victimization was negatively correlated with cultural salience, which contrasts starkly with the positive sign accompanying conflict exposure. This suggests that people respond differently to conflict exposure and the concrete experience of violence. State capacity was significant at the one percent level and carried a negative sign. This suggests that the perception that the police is doing a good job at providing security lowers the probability of people choosing either their ethnicity or religion as the most important aspect of their identity. Put differently, cultural salience is likely to diminish if people think the police is effectively playing its role of providing security. Models 3 and 4 show that these results are robust to alternative operationalizations of conflict based on the

UCDP and GTD datasets. Suffice it to add that the results reported in Table 3 are also robust to a different measure of conflict where the buffers have a radius of 5km (see Table A3 in the appendix).

However, while ingroup cohesion could be beneficial in the sense that it serves as a buffer against conflict-induced existential anxieties, hence enabling people to carry on with their "normal" lives despite the prevalence of conflict, it could also be problematic because it allows people to overcome the challenges associated with collective action, which makes mobilization in conflict situations easy. Such mobilizations might be driven by the motivation of exacting revenge, which in turn could lead to a downward spiral whereby each attack creates the conditions for a reprisal. This is especially relevant in scenarios where the population is polarized along ethnoreligious lines and cultural groups are highly entitative. These elements are present in the case study, which might explain why Kaduna has a particularly high level of intercommunal violence characterized by reprisal attacks (e.g., Tuki 2023). Schaub (2014, p. 19) succinctly described this phenomenon: "Rather than being an indicator of 'social capital,' cooperation in the context of communal violence is driven by a form of potentially aggressive 'solidarity with a sharp edge.'"

5. Conclusion

This study examined the effect of exposure to violent conflict on expected victimization among the population in the Northern Nigerian state of Kaduna, which has the second highest incidence of violent conflict out of Nigeria's 36 states. The regression results showed that a curvilinear relationship exists between conflict exposure and expected victimization. This relationship, which is akin to an inverted "U", suggests that at the initial stage of conflict exposure, people worry that they will be victimized. As conflict exposure increases, so does the fear of being victimized, until a point is reached at which expected victimization peaks. Further exposure to conflict beyond the peak rather leads to a decline in expected victimization. One explanation for the decline in expected victimization after the peak, which I was able to show with the data, is that the existential threat posed by violent conflict strengthens ingroup cohesion by prompting people to rely more heavily upon their ethnoreligious kinship ties for material and non-material support. This suggests that although violent conflict shatters peoples' sense of security and instills fear, they eventually devise ways to carry on with their "normal" lives despite the conflict.

Yet, while the strengthening of ingroup cohesion as a result of conflict exposure could be beneficial in that it engenders resilience and recovery, it could also be problematic. This is because increased cohesion among ingroup members could make intergroup boundaries more salient, which in turn could heighten the risk of intergroup conflicts. This is especially relevant in the case of Kaduna which has a long history of religiously-motivated conflicts, and where ethnoreligious groups are characterized by high entitativity.

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Conflict of interest:

None.

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Ethical approval:

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Appendix

Section A

Table A1: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Expected victimization†	1298	1.19	1.359	0	4
Expected victimization (binary)	1298	0.233	0.423	0	1
Conflict (10km)	1353	31.29	48.968	0	139
Conflict (5km)	1353	14.376	32.874	0	125
Conflict [UCDP] (10km)	1353	10.934	17.906	0	48
Conflict [UCDP] (5km)	1353	5.19	12.996	0	47
Conflict [GTD] (10km)	1353	14.534	20.671	0	60
Conflict [GTD] (5km)	1353	6.429	12.609	0	49
Conflict square (10km)$^{\sigma}$	1353	4.247	3.49	0	9.883
Conflict square (5km)$^{\sigma}$	1353	2.767	2.97	0	9.673
Conflict square [UCDP] (10km)$^{\sigma}$	1353	2.69	2.951	0	7.784
Conflict square [UCDP] (5km)$^{\sigma}$	1353	1.454	2.402	0	7.742
Conflict square [GTD] (10km)$^{\sigma}$	1353	3.527	2.931	0	8.222
Conflict square [GTD] (5km)$^{\sigma}$	1353	2.189	2.465	0	7.824
Victimization	1298	0.179	0.383	0	1
State capacity	1298	2.492	1.577	0	4
Gun proliferation	1298	1.106	0.933	0	2
Household income	1298	0.978	0.921	0	4
Age	1321	34.391	14.004	15	85
Gender	1321	0.557	0.497	0	1
Marital status	1298	0.74	0.439	0	1
Cultural salience	1298	0.79	0.407	0	1

Note: † is the dependent variable, "expected victimization (binary)" is a reduced form of the dependent variable where its five response categories were collapsed into two main categories. σ denotes variables that have been logged.

Table A2: Replicating the results in Table 1 using 5km buffer

Expected victimization†	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Conflict square	-0.034***	-0.043***	-0.048***	-0.011***		
	(0.012)	(0.012)	(0.012)	(0.004)		
Conflict square [UCDP]					-0.046***	
					(0.014)	
Conflict square [GTD]						-0.027*
						(0.014)
Past victimization		0.345***	0.353***	0.109***	0.327***	0.347***
		(0.103)	(0.103)	(0.033)	(0.103)	(0.103)
State capacity		-0.08***	-0.08***	-0.02***	-0.076***	-0.076***
		(0.025)	(0.025)	(0.008)	(0.025)	(0.025)
Gun proliferation		0.106***	0.107***	0.033***	0.106***	0.102**
		(0.04)	(0.041)	(0.013)	(0.041)	(0.041)
Household income			0.025	-0.002	0.03	0.018
			(0.041)	(0.013)	(0.041)	(0.041)
Age			0.002	0.00	0.001	0.001
			(0.003)	(0.001)	(0.003)	(0.003)
Gender			0.111	0.019	0.099	0.102
			(0.079)	(0.025)	(0.079)	(0.079)
Marital status			-0.152	-0.045	-0.113	-0.116
			(0.106)	(0.032)	(0.103)	(0.106)
Constant	1.284***	1.326***	1.297***	0.299***	1.219***	1.225***
	(0.051)	(0.099)	(0.16)	(0.048)	(0.156)	(0.16)
Estimation method	OLS	OLS	OLS	LPM	OLS	OLS
Observations	1298	1298	1298	1298	1298	1298
R-squared	0.006	0.031	0.034	0.028	0.03	00.026
AIC statistic	4475.86	4448.204	4452.396	1431.808	4457.387	4462.98
BIC statistic	4486.197	4474.047	4498.913	1478.325	4503.905	4509.498

Note: Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1, †is the dependent variable, violent conflict is measured using buffers with a 5km radius. All models are estimated using ordinary least squares (OLS) regression except for model 4 which is estimated using linear probability model (LPM). The dependent variable is measured on a scale with five ordinal categories in all the models, except for model 4 where it is measured binarily. The explanatory variable in model 6 had a p-value of 0.13.

Table A3: Replicating the results in Table 2 using 5km buffer

Cultural salience†	**(1)**	**(2)**	**(3)**	**(4)**
Conflict	0.001***	0.001***		
	(0.00)	(0.00)		
Conflict square [UCDP]			0.002***	
			(0.001)	
Conflict square [GTD]				0.002***
				(0.001)
Past victimization		-0.087***	-0.086***	-0.089***
		(0.032)	(0.032)	(0.032)
State capacity		-0.025***	-0.025***	-0.025***
		(0.007)	(0.007)	(0.007)
Gun proliferation		-0.002	-0.002	-0.001
		(0.012)	(0.012)	(0.012)
Constant	0.776***	0.858***	0.859***	0.855***
	(0.013)	(0.026)	(0.026)	(0.026)
Estimation method	LPM	LPM	LPM	LPM
Observations	1298	1298	1298	1298
R-squared	0.006	0.021	0.021	0.021
AIC statistic	1345.507	1331.744	1332.292	1332.303
BIC statistic	1355.845	1357.587	1358.135	1358.145

Note: Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1, † is the dependent variable, violent conflict is measured using buffers with a 5km radius. All regressions are estimated using linear probability model (LPM). Cultural salience is a dummy variable that takes the value of 1 if respondent attach more importance to either their religion or ethnicity than their nationality.

Section B

Sampling strategy

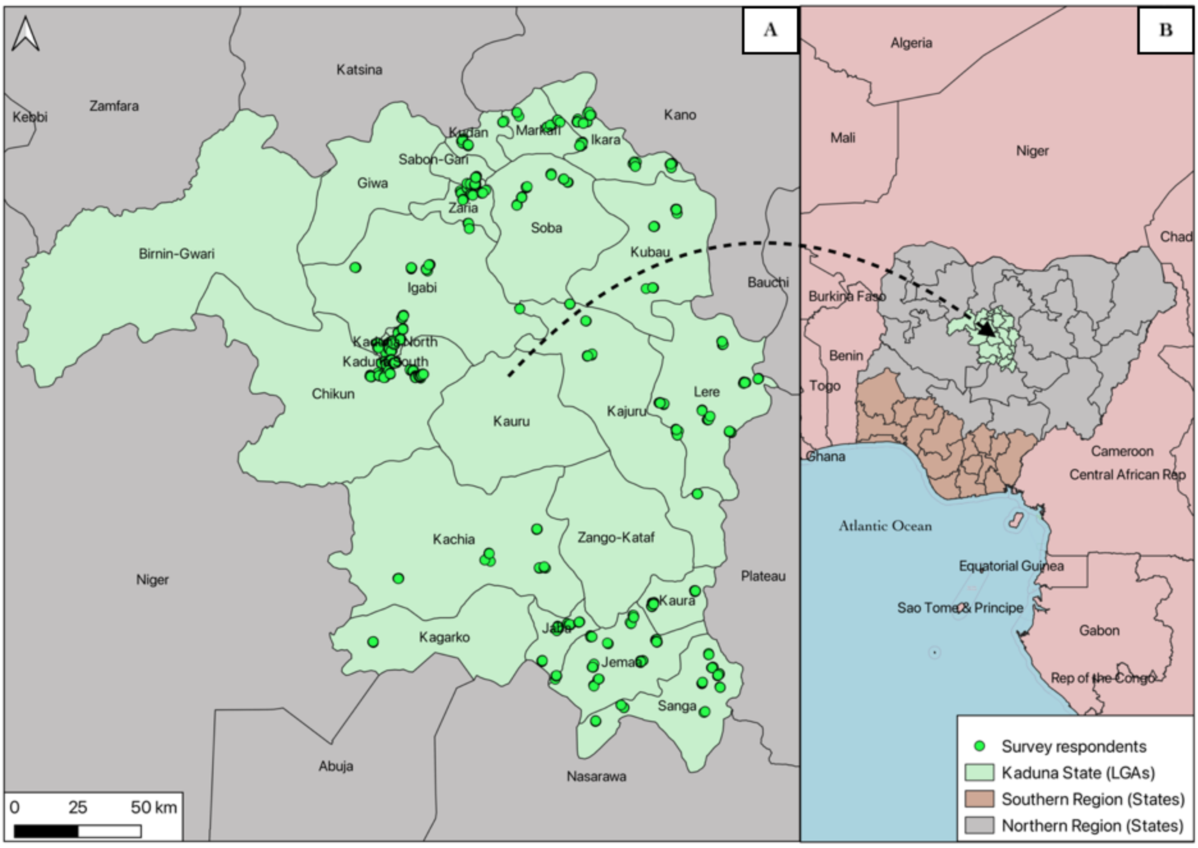

Figure B1: Study area and respondents' geolocations

Note: Panel A shows the geolocations of the survey respondents and the administrative boundaries of the local government areas (LGAs) (i.e., municipalities) in the state of Kaduna. Panel B shows the state boundaries within Nigeria's two major regions—i.e., the Northern and Southern Regions. The shapefiles containing Nigeria's administrative boundaries were developed by the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA).

As part of the Transnational Perspectives on Migration and integration (TRANSMIT) research project, the WZB Berlin Social Science Center, Germany, conducted a survey in the Northern Nigerian state of Kaduna in 2021. A total of 1,353 respondents were interviewed in the state. To select the interview locations, multi-stage clustered random sampling was employed. Four out of the 23 local government areas (LGAs) (i.e., municipalities) in Kaduna (i.e., Giwa, Birnin Gwari, Kauru, and Zangon Kataf) were unsafe areas for interviews due to the high risk of intercommunal conflict. They were excluded from the sampling frame.

Grid cells of 5 x 5km, which were called precincts, were developed using QGIS software. These precincts were laid on a shapefile showing Kaduna state's administrative boundaries. Each

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precinct was comprised of smaller 0.5 x 0.5km grid cells. 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. Respondents were at least 15 years old. Before minors were interviewed, consent was sought from the household head. The minor was interviewed only if he or she also granted consent. Respondents were informed that participation in the survey was voluntary, and they could opt out of the interview at any time.

The ensure that the exclusion of the four unsafe LGAs did not skew the sample, the sample was stratified according to the population size in the senatorial district (Each state in Nigeria comprises of 3 senatorial districts; each senatorial district comprises of LGAs). Samples were drawn within each of the senatorial districts in relation to their respective population shares. 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 data used for the sampling were obtained from the 2020 Worldpop gridded dataset (Bondarenko et al. 2020).