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Assessing the impact of violent conflict on attitudes toward military rule in Nigeria

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Abstract

Violent conflict is often assumed to undermine democratic legitimacy and increase public support for authoritarian alternatives. Yet empirical evidence remains limited, particularly in the context of developing democracies. This study examines how exposure to violent conflict shapes regime preferences in Nigeria, Africa's largest democracy and a country persistently affected by insurgency, intercommunal violence, and state fragility. Using data from Round 9 of the Afrobarometer survey and an instrumental variable strategy that leverages proximity to international borders as a source of exogenous variation in conflict exposure, I identify the causal effect of violence on public attitudes toward military rule. Contrary to conventional expectations, the results show that individuals exposed to higher levels of violence are significantly less likely to support a military takeover. These findings challenge prevailing assumptions about insecurity and authoritarian appeal. The study contributes to broader debates on regime legitimacy and authoritarian attitudes in fragile states.

Keywords

Nigeria, Military rule, Authoritarianism, Democracy, Violent conflict, Governance

JEL Classifications

D72, D74, P16

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1. Introduction

The recent wave of coups across Africa's Sahel region has significantly undermined the legitimacy of several democratic governments. The rise of military regimes in countries such as Mali, Burkina Faso, and Niger has sparked a growing body of research investigating the factors underlying this phenomenon (e.g., Bøås & Haavik 2025; Engels 2025, 2023; Bester 2024; Tuki 2024; McCullough and Sandor 2024). Notably, these military juntas have justified their takeovers by citing the failure of elected governments to effectively address widespread insecurity (Bøås & Haavik 2025; Hassan 2024; McCullough and Sandor 2024; Aina 2023).

This troubling trend of democratic erosion has drawn strong condemnation from regional organizations such as the Economic Community of West African States (ECOWAS) and the African Union (AU) (ECOWAS 2023; African Union 2023). In response to the 2023 coup in the Republic of Niger, ECOWAS—under the leadership of Nigerian President Bola Ahmed Tinubu—issued a stern ultimatum to the ruling military junta, threatening military intervention if the democratically elected government of Mohammed Bazoum was not reinstated within one week (Krippahl 2023). In addition to this threat, ECOWAS and the AU imposed economic and diplomatic sanctions on the affected countries (Mali, Burkina Faso, and Niger) (Sahara Reporters 2023; Asadu 2023; Obiezu 2023) and suspended them from the bloc, prompting their eventual exit (Ewokor 2025; International Crisis Group 2024).

While ECOWAS's commitment to upholding democratic norms is commendable, its swift resort to the threat of military intervention following the coup in Niger may have been too hasty (Olawunmi 2023). Rather than prioritizing dialogue or diplomatic engagement, the bloc issued a military ultimatum that was ultimately ignored by the junta—and not enforced after the deadline passed. Despite the absence of direct intervention, the military-led countries remain largely isolated within the region. In defiance, these states have responded by forming a new alliance, signaling a deepening rift between them and the broader regional democratic order (Mwangi 2025; North Africa Post 2025; APA News 2025).

During the standoff between ECOWAS and the military junta in Niger, President Tinubu's threat to intervene militarily drew strong criticism from many Nigerians, including members of the Senate (Olawunmi 2023; Orjinmo 2023; Peltier & Alfa 2023). Critics argued that he was attempting to resolve a crisis in a neighboring country while failing to adequately address the persistent insecurity plaguing Nigeria itself. Moreover, Tinubu's presidency—which was only two months old at the time—was still being challenged in court by the opposition over allegations of electoral irregularities (Hassan 2024; Olawunmi 2023).

Insecurity has remained a major challenge in Nigeria over the past decade. Data from the Armed Conflict Location and Event Data Project (ACLED) (Raleigh et al. 2010) reveal a generally upward trend in violent conflict incidents since 2016.² Notably, 2023—the year President Tinubu issued the military threat against Niger—was marked by 3,286 violent incidents and 8,515 associated fatalities. The following year, 2024, was even more devastating, recording 4,085 incidents and 9,517 fatalities—making it Nigeria's most violent year since 1997. In fact, the Republic of Niger is home to about 300,000 Nigerian refugees, who have fled attacks perpetrated by terrorist groups (Akinkuotu 2023). These stylized facts underscore the Nigerian government's ongoing failure to fulfill one of its most basic responsibilities: ensuring the security of its own citizens.

Despite the persistence of violent conflict across Nigeria—ranging from the *Boko Haram* insurgency in the northeastern region (Tuki 2025; Anugwom 2019; Onuoha 2012), to armed banditry in the northwest (Ojo et al. 2023; Aina et al. 2023; Ejiofor 2022), to recurring clashes between herders and farmers in the Middle Belt (Tuki 2024a, 2023; Nwankwo 2024)—there is limited research on how such violence shapes public attitudes toward alternatives to democratic institutions. This study examines how exposure to violent conflict influences Nigerians' support for military rule, drawing on nationally representative data from Round 9 of the Afrobarometer survey ($n = 1,600$). To measure violent conflict, I compute the cumulative number of violent

² Violent conflicts are defined as incidents categorized as battles, violence against civilians, and explosions or remote violence. This means that events involving lower levels of violence—such as protests, riots, and strategic developments—were excluded from the analysis.

incidents within a 10 km radius of respondents' geolocations. Attitudes toward military rule are assessed using an item in the Afrobarometer survey that asks respondents whether they approve or disapprove of military rule, with responses measured on a five-point ordinal scale ranging from "1 = Strongly disapprove" to "5 = Strongly approve." To address concerns of endogeneity, I employ an instrumental variable strategy that leverages geographic proximity to Nigeria's international borders as a source of exogenous variation in conflict exposure.

The findings reveal a counterintuitive dynamic: Nigerians who experience higher levels of violence are significantly less likely to support military rule. These results challenge common assumptions that sustained exposure to violence may lead to authoritarian appeals (e.g., Tuki 2024; Bester 2024). This study contributes to broader debates on regime legitimacy and civil-military relations in African states facing chronic insecurity (e.g., Engels 2025; Tuki 2024; Bester 2024; McCullough & Sandor 2023).

The remainder of this study is structured as follows. The next section introduces the data and operationalizes the variables used in the regression models, along with a discussion of the empirical strategy. This is followed by a presentation and discussion of the regression results. The final section summarizes the key findings and concludes the study.

2. Data and methodology

This study relies on data from Round 9 of the Afrobarometer survey, collected in Nigeria in 2022 ($n = 1,600$).³ The survey covers Nigeria's 36 states and the Federal Capital Territory (Abuja). Because Afrobarometer employs probabilistic sampling, the data are representative of Nigeria's population.⁴ Respondents were at least 18 years old, with males and females equally represented in the sample (in a 50:50 ratio).

³ To access the Afrobarometer data and the survey questionnaire visit: <https://www.afrobarometer.org/>

⁴ For more information on Afrobarometer's sampling strategy visit: <https://www.afrobarometer.org/surveys-and-methods/sampling/>

2.1. Operationalization of the variables

2.1.1. Dependent variable

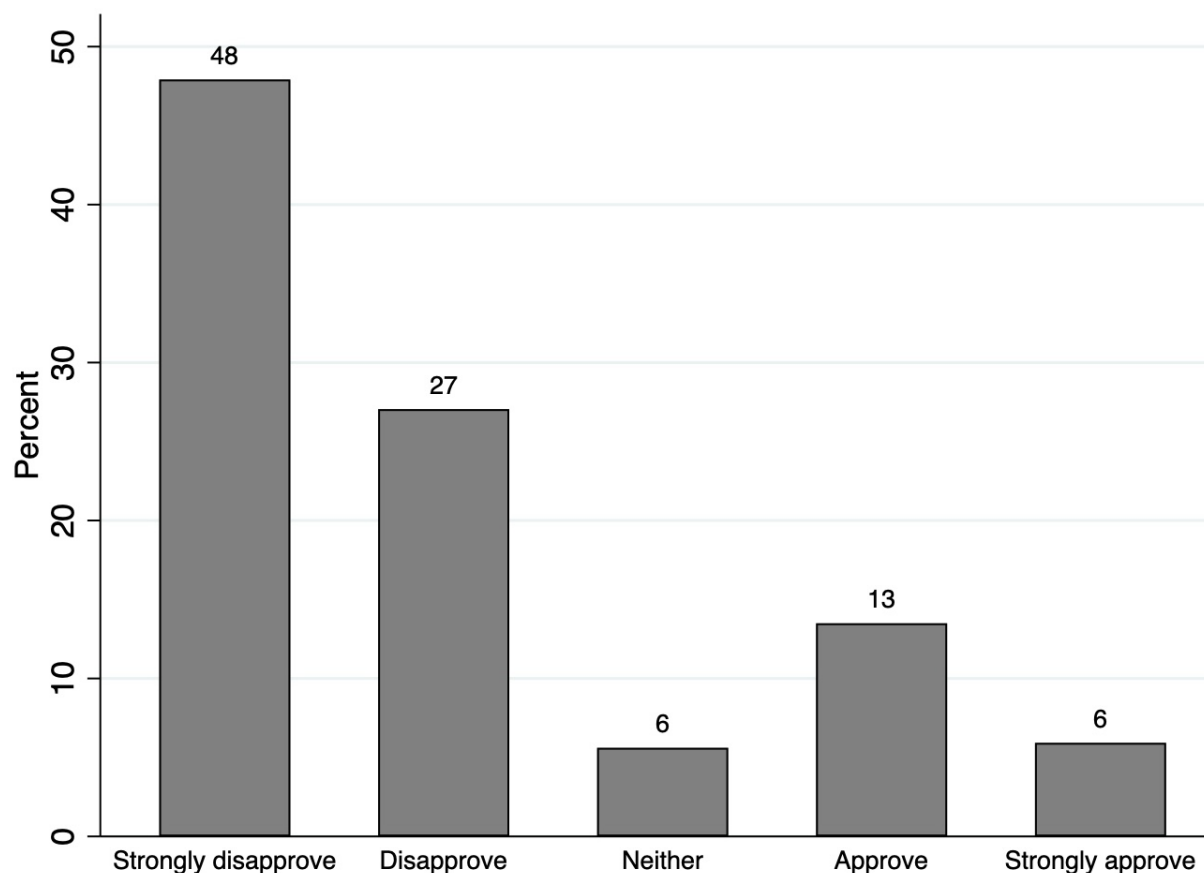


Figure 1: Nigerians' attitudes toward military rule

Note: The figure illustrates Nigerians' attitudes toward military rule using data from Round 9 of the Afrobarometer survey, conducted in Nigeria in 2022. The horizontal axis represents the varying levels of support for military rule, while the vertical axis indicates the percentage of respondents at each level.

The dependent variable—*Military rule*—captures the extent to which respondents endorse military governance. It is based on the Afrobarometer survey question: “*There are many ways to govern a country. Would you disapprove or approve of the following alternatives? The army comes in to govern the country.*” Responses were recorded on a five-point ordinal scale, ranging from “1 = Strongly disapprove” to “5 = Strongly approve.” 14 respondents who refused to answer this question were coded as missing, resulting in a slight reduction in the overall sample size. This coding approach was consistently applied to all variables derived from the Afrobarometer data. As shown in Figure 1, the majority of Nigerians oppose military rule: 75% either disapprove or strongly disapprove, while 19% express approval or strong approval. An additional 6% report a neutral or indifferent stance.

2.1.2. Explanatory variable

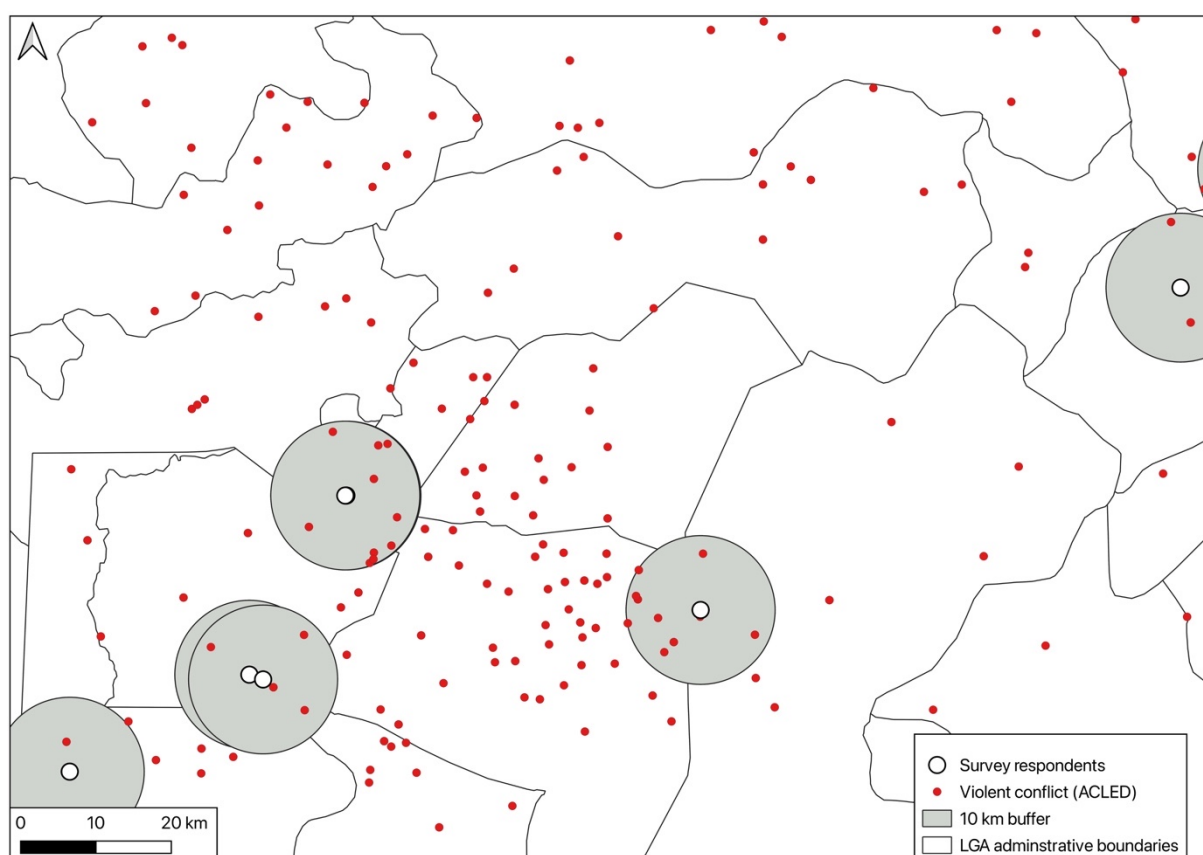


Figure 2: Measuring conflict exposure

Note: The figure displays the geolocations of hypothetical respondents, along with a 30-kilometer buffer surrounding their dwellings and the administrative boundaries of the local government areas (LGAs) (i.e., municipalities) in which they reside.

The explanatory variable—*Conflict*—captures the total number of violent incidents that occurred within a 10-kilometer radius of respondents' dwellings between 1997 and 2021 (see Figure 2). The data come from the Armed Conflict Location and Event Data Project (ACLED) (Raleigh et al. 2010).⁵ In this context, violent conflict is defined as any incident classified under one of three categories: battles, violence against civilians, and explosions/remote violence. This definition intentionally excludes lower-intensity events such as protests, riots, and strategic developments. The time frame of 1997 to 2021 was selected to capture the cumulative impact of conflict exposure, in line with research suggesting that the effects of violent conflict tend to persist over time (e.g., Barceló 2021; Tuki 2025a, 2024b). The start year of 1997 reflects the earliest available year of ACLED data, while the end year of 2021 was chosen to create a one-year lag relative to the

⁵ To access the ACLED dataset visit: <https://acleddata.com/>

Afrobarometer survey, which was conducted in 2022. This lag helps mitigate concerns about reverse causality between conflict exposure and support for military rule

Measuring conflict exposure using spatial buffers is more effective than relying on administrative boundaries, such as local government area (LGA) (i.e., municipalities). If I had used LGAs, all respondents within a given area would have been assigned the same level of conflict exposure—namely, the total number of incidents within that unit. This approach would have significantly reduced variation in the explanatory variable, limiting its analytical power. Furthermore, administrative boundaries in Nigeria are often poorly defined, making them a less reliable basis for spatial analysis. By contrast, using a 10-kilometer buffer around each respondent's location allows for a more precise and individualized measure of conflict exposure.⁶ According to this approach, 89% of respondents experienced at least one violent incident within their buffer zone, and 40% experienced 10 or more incidents.

To ensure the robustness of my findings and mitigate potential bias from relying on a single data source, I constructed alternative versions of the conflict exposure variable using two additional datasets: the Uppsala Conflict Data Program Georeferenced Events Dataset (UCDP-GED) (Sundberg & Melander 2013)⁷ and the Global Terrorism Dataset (GTD) (National Consortium for the Study of Terrorism and Responses to Terrorism 2022).⁸ In contrast to the ACLED dataset, which begins in 1997, the UCDP-GED and GTD datasets have earlier start years—1989 and 1970, respectively. As such, the conflict exposure variables derived from these sources capture incidents occurring within a 10-kilometer buffer around each respondent's location, starting from the respective dataset's inception year.⁹ The datasets also differ in their inclusion criteria. The UCDP-GED only records events that resulted in at least one fatality, whereas ACLED and GTD include

⁶ I also created alternative versions of the explanatory variable using buffers with radii of 20 km and 30 km. These variables were used to conduct a robustness check.

⁷ To access the UCDP-GED dataset visit: <https://ucdp.uu.se/>

⁸ To access the GTD dataset visit: <https://www.start.umd.edu/gtd/>

⁹ While the variable based on the UCDP dataset has a lag of one year, that derived from GTD has a deeper lag of 2 years because the data are only available until 2020.

incidents regardless of whether fatalities occurred. It is also important to note that the GTD is specifically limited to terrorist attacks, defined as “the threatened or actual use of illegal force and violence by a nonstate actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation” (GTD Codebook 2021, p. 11).

2.1.3. Control variables

I include a range of control variables that may confound the relationship between conflict exposure and support for military rule. These controls account for factors such as economic development, demographic characteristics, and political attitudes. They include mean nighttime light intensity, population, urban residence, trust in democratic institutions, trust in the army, perceived government corruption, poverty, educational attainment, age, and gender. Section B in the appendix provides a detailed description of each variable, while Table A1, also in the appendix, presents summary statistics for all the variables used to estimate the regression model.

2.2. Empirical strategy

Although this study focuses on how violent conflict influences attitudes toward military rule, it is also plausible that support for military rule could itself foster a greater propensity for violence. Individuals who favor military rule often harbor deep distrust toward civilian institutions such as courts or parliaments. As a result, they may be more inclined to endorse extrajudicial or violent actions as viable alternatives to what they perceive as ineffective or corrupt processes. Furthermore, military regimes tend to normalize the use of force in governance. Supporters of such regimes may internalize this norm, viewing violence not as a last resort but as an acceptable—even efficient—means of resolving conflict. To mitigate concerns about reverse causation, I lag the key explanatory variable by one year, considering only instances of violent conflict that occurred prior to the survey. This approach assumes that present attitudes are unlikely to influence past exposure to violence. Nevertheless, the risk of omitted variable bias remains, given the difficulty of accounting for all potential confounders in the relationship between conflict exposure and support for military rule. To address this, I employ an instrumental variable strategy.

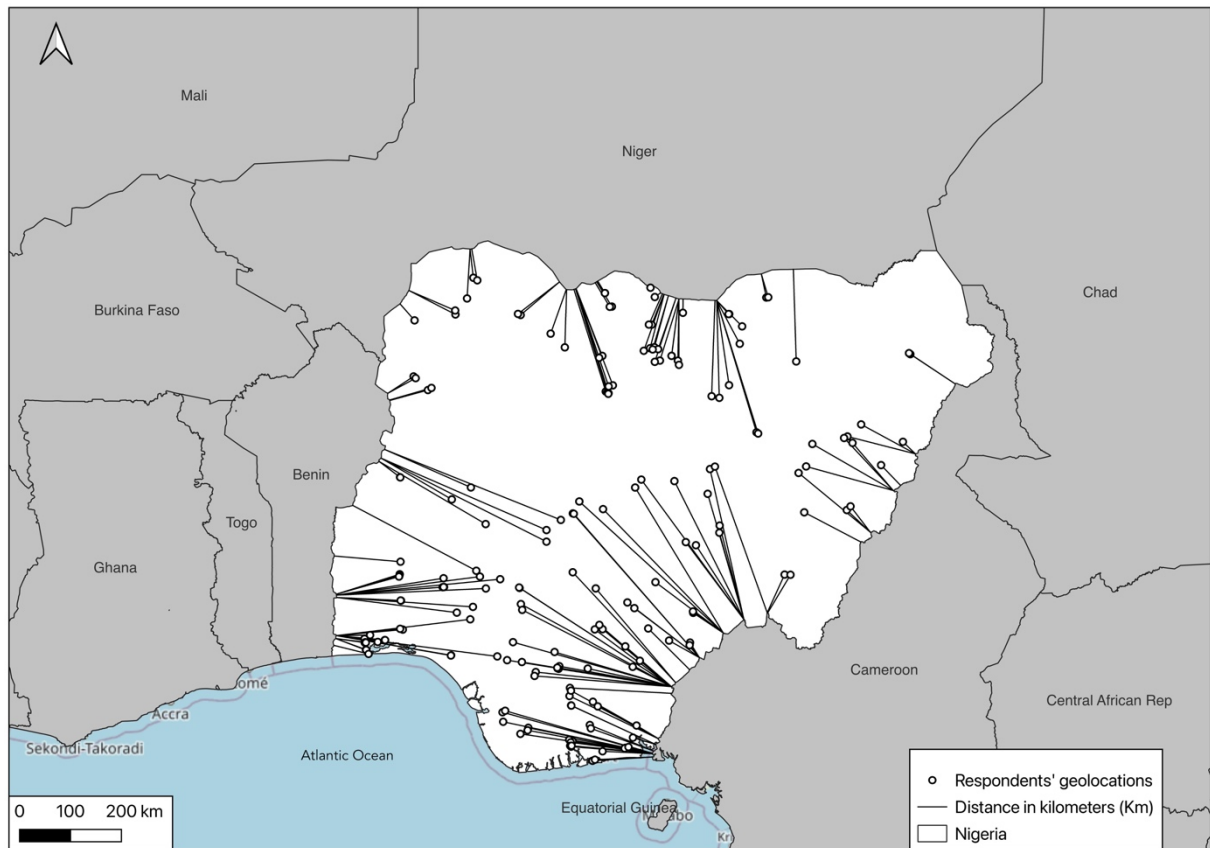


Figure 3: Measuring distance from respondents' geolocations to the border

Note: The figure shows the geolocations of the survey respondents, along with lines depicting the straight-line (as-the-crow-flies) distance from each respondent's location to the nearest international land border. Distances are measured in kilometers.

The instrumental variable strategy is implemented in two stages. In the first stage, I instrument exposure to violent conflict using the distance from respondents' dwellings (see Figure 3) to Nigeria's nearest international land border—regressing conflict exposure on this distance measure. In the second stage, I regress the dependent variable—attitudes toward military rule—on the predicted values of conflict exposure obtained from the first stage. The rationale for using distance to the border as an instrument is that proximity to international borders is plausibly associated with a higher risk of violent conflict. Border regions in Nigeria often suffer from limited state capacity, as they tend to be far from the administrative center and receive less oversight and public investment (Le Billon 2001). This limited government presence can create a power vacuum, allowing armed groups to operate with relative impunity and, in some cases, establish parallel governance structures that undermine the authority of the state (Buba 2023; Ejiofor 2025).

Furthermore, proximity to international borders—particularly in areas with weak state capacity—is often associated with a higher concentration of small arms and light weapons (SALW), which can significantly increase the risk of violent conflict. Since the collapse of Libya in 2011 following NATO intervention, large quantities of SALW have circulated across the Sahel region, fueling instability and armed violence (Chávez & Swed 2024; Strazzari & Tholens 2014). This problem has been exacerbated by the porous borders between countries in the region, which facilitate the unchecked movement of weapons, militants, and other illicit actors. These dynamics are especially pronounced in border areas where state capacity—defined as the government’s ability to exert control and enforce order—is typically limited due to underdeveloped infrastructure and minimal institutional presence. As a result, such regions often become hubs for arms proliferation and violent activity. A clear example is Borno State, which borders Cameroon, Chad, and Niger, and has long served as a stronghold for the radical Islamist group Boko Haram (Anugwom 2019; Onuoha 2012). Similarly, Zamfara State—bordering Niger—has experienced a particularly high incidence of banditry and ransom-driven abductions, underscoring the link between border proximity, arms proliferation, and violent conflict (BBC 2024; Idris et al. 2024; Bello 2025; Saminu et al. 2023).

However, one potential concern is that distance to the border may be correlated with population size and urbanization. For example, democratic governments may be less inclined to invest in infrastructure or public services in sparsely populated border regions, which could, in turn, shape local attitudes toward military rule. Furthermore, rural areas are typically poorer than urban centers and tend to have less government presence. To address these potential sources of bias, I control for population size within a 10-kilometer buffer zone around respondents’ geolocations and include a dummy variable, derived from the Afrobarometer survey, coded as 1 if a respondent lives in an urban center and 0 if they live in a rural area. Additionally, I include state fixed effects in some regression models to account for unobserved, time-invariant factors that may

influence both conflict exposure and political attitudes. These factors may include cultural norms, historical patterns of political marginalization, or other state-specific characteristics.

One concern is that the correlation between proximity to the border and violent conflict may be driven primarily by respondents living very close to the border. To address this, I estimated a series of alternative models restricting the sample to respondents residing at least 50 km and 100 km away from the border, respectively. A second concern relates to the measurement of violent conflict over a long time span (1997 to 2021), which could be problematic if earlier conflicts prompted migration. However, if the mechanism through which exposure to violence shapes attitudes toward military rule operates via the formation of communal norms, then long-term exposure may still be relevant. Individuals may internalize local norms over time, even if they were not present during earlier conflicts. Nevertheless, to guard against potential bias, I estimated additional models restricting the conflict measure to a shorter reference period—specifically, the five years preceding the survey (2017 to 2021) and the two years preceding the survey (2020 to 2021).

To examine the causal effect of violent conflict on attitudes toward military rule, I consider two models of the following general forms:

$$Conflict_i = \alpha_0 + \alpha_1 Distance\ to\ border_i + e_i \quad (1)$$

$$Military\ rule_{ij} = \beta_0 + \beta_1 Conflict_i^* + \beta_2 \varphi'_i + \tau_j + \mu_i \quad (2)$$

In equation (1), $Conflict_i$ indicates a count of the cumulative number of violent conflict incidents within a 10 km radius of Respondent i 's dwelling who lives in state j , α_0 is the intercept, $Distance\ to\ border_i$ measures the distance from the respondent's geolocation to Nigeria's nearest land border as-crow-flies and in kilometers, α_1 is the coefficient for the distance variable, while e_i is the error term. In equation (2), $Military\ rule_i$, which is the main dependent variable, measures Respondent i 's support for military rule, $Conflict_i^*$ denotes the predicted value of conflict exposure derived from equation (1), β_0 is the intercept, β_1 and β_2 are the coefficients of the explanatory and control variables, respectively, φ' is a vector of control variables discussed

earlier, τ_j denotes state fixed effects, which account for time-invariant factors that are unique to the respective states in which respondents reside such as geographical terrain, climate, and cultural norms, while μ_i denote the error terms.

I conducted the analysis using a two-step approach. In the first step, I examined the correlation between conflict exposure and attitudes toward military rule by estimating an ordered probit regression model. This method is appropriate because it accounts for the ordinal nature of the dependent variable. In the second step, I estimated an instrumental variable (IV) model to identify the causal effect of conflict exposure on attitudes toward military rule. Specifically, I employed the instrumental variable ordered probit (IVOpbit) regression, which not only respects the ordered structure of the outcome variable but also enables estimation of the treatment effect across each category of the dependent variable. The identification strategy relies on the assumption that distance to the nearest international border affects attitudes toward military rule only through its impact on exposure to violent conflict.

3. Results and discussion

3.1. Correlational analysis

Table 1: Ordered probit models regressing attitudes toward military rule on violent conflict

Military rule	(1)	(2)	(3)
Conflict [†]	-0.002*** (0.00)	-0.001** (0.00)	-0.001* (0.001)
Intercept 1	-0.124*** (0.034)	-0.743 (0.466)	1.288 (0.949)
Intercept 2	0.609*** (0.036)	0.009 (0.464)	2.086** (0.95)
Intercept 3	0.8*** (0.038)	0.196 (0.465)	2.284** (0.951)
Intercept 4	1.502*** (0.051)	0.869* (0.467)	2.992*** (0.953)
Control variables	No	Yes	Yes
State fixed effects	No	No	Yes
Observations	1586	1456	1456
Pseudo R²	0.007	0.015	0.051
Log pseudolikelihood	-2057.143	-1864.559	-1795.677
AIC statistic	4124.286	3759.117	3693.354
BIC statistic	4151.13	3838.369	3962.81

Note: Robust standard errors are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All models are estimated using ordered probit (OPbit) regression. [†] denotes the explanatory variable, which is measured using buffers with a radius of 10 km. Control variables include nighttime light, population, urban residence, trust in government, trust in the army, perceived government corruption, index, educational level, age, and gender. AIC = Akaike information

criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted in Nigeria in 2022.

I begin with a simple correlational analysis in which I examine the association between violent conflict and attitudes toward military rule. Table 1 reports the results. In Model 1, which includes only the conflict variable, the coefficient is negative and statistically significant at the 1% level, indicating a strong negative association between exposure to violent conflict and support for military rule. Model 2 introduces a set of control variables; although the conflict coefficient remains negative, its statistical significance declines to the 5% level. In Model 3, which includes fixed effects for the states where respondents reside, violent conflict still maintains a negative coefficient, although its statistical significance drops to 10%. It is important to note, however, that these findings are purely correlational and do not address potential endogeneity concerns.

3.2. Instrumental variable regression analysis

Table 2: Instrumental variable regression models examining the effect of violent conflict on attitudes toward military rule

Dependent variables:				
	Conflict	Military rule		
	1st-stage	2nd-stage		
	(1)	(2)	(3)	(4)
	OLS	IVOProbit	IVOProbit	IVOProbit
Conflict†		-0.008*** (0.001)	-0.009*** (0.001)	-0.01*** (0.001)
Distance to border (Km)	-0.108*** (0.018)			
Constant	61.458*** (4.843)			
Intercept 1		-0.406*** (0.053)	-0.745** (0.294)	-0.052 (0.48)
Intercept 2		0.124 (0.135)	-0.303 (0.294)	0.296 (0.561)
Intercept 3		0.261* (0.158)	-0.193 (0.3)	0.382 (0.584)
Intercept 4		0.769*** (0.242)	0.203 (0.338)	0.691 (0.673)
Control variables	No	No	Yes	Yes
State Fixed effects	No	No	No	Yes
Observations	1600	1586	1456	1456
R-squared	0.012			
Log pseudolikelihood		-11523.774	-10550.548	-10487.536
Error terms correlation		0.694***	0.811***	0.9***
AIC statistic	19109.11	23065.55	21139.1	21085.07
BIC statistic	19119.87	23113.87	21239.48	21375.66

Note: Robust standard errors are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Model 1, the first-stage regression, is estimated using ordinary least squares (OLS) regression, while Models 2, 3, and 4, the second-stage regressions, are estimated using instrumental variable ordered probit (IVOProbit) regression. † denotes the explanatory variable, which is measured using buffers with a radius of 10 km. Control variables include nighttime light, population, urban residence, trust in government, trust in the army, perceived government corruption, index, educational level, age, and gender. The regression models are based on data from Round 9 of the Afrobarometer

To move towards a causal claim, I estimate a series of instrumental variable ordered probit (IVOpbit) models. Table 2 reports the results. In the first-stage regression (Model 1), I regress exposure to violent conflict on the instrumental variable—distance to the nearest national land border. I estimate this model using ordinary least squares (OLS) regression because both variables are continuous. As anticipated in the empirical strategy (Section 2.2), the distance variable has a negative coefficient that is statistically significant at the 1% level. This indicates that individuals living closer to national borders are more likely to be exposed to violent conflict. In other words, proximity to the border is associated with a higher risk of conflict exposure. In the second-stage regression models (Models 2, 3, and 4), I use the predicted values of conflict obtained from Model 1 as the explanatory variable. In Model 2, which includes only the predicted value of violent conflict, the variable also has a negative coefficient, indicating that exposure to violent conflict reduces support for military rule. The correlation between the error terms of the first- and second-stage regressions is statistically significant at the 1% level, indicating that endogeneity was indeed present and the use of an instrumental variable approach in estimating the model is appropriate. The main finding showing the negative effect of conflict exposure on support for military rule remains robust with the inclusion of control variables in Model 3, and with the addition of state fixed effects in Model 4.

To assess whether the results reported in Table 1 are sensitive to the source of conflict data, I replicated the analysis using alternative measures of conflict exposure derived from the Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP-GED) and the Global Terrorism Dataset (GTD). As shown in Tables A2 and A3 in the appendix, the findings remain consistent, suggesting that the results are not biased by the choice of data source. Additionally, I extend the analysis by shifting the focus from the incidence of conflict to its intensity, measured by the total number of fatalities associated with conflict events within a 10-kilometer radius of respondents' dwellings. The results, presented in Table A4, indicate that conflict intensity also has a negative effect on support for military rule.

Furthermore, I re-estimated the models using larger buffer zones—specifically, 20 km and 30 km radii—to measure conflict exposure. The findings, reported in Tables A5 and A6 in the appendix, remain consistent with those in Table 1, reinforcing the reliability of the main results. To ensure that the results are not driven by respondents living very close to international borders—who may have disproportionately high exposure to conflict—I estimated models restricting the sample to individuals residing at least 50 km and 100 km from the border, respectively. As shown in Tables A7 and A8 in the appendix, the results remain robust. As a final robustness check, I employed alternative measures of conflict exposure based on incidents occurring within a 10 km radius of respondents' dwellings, using two shorter reference periods: the five years prior to the survey (2017–2021) and the two years prior to the survey (2020–2021). This adjustment addresses potential concerns related to the original, longer measurement window (1997–2021), which may be problematic if earlier conflicts prompted migration. Tables A9 and A10 confirm that the findings are robust even when conflict exposure is measured over these shorter time frames.

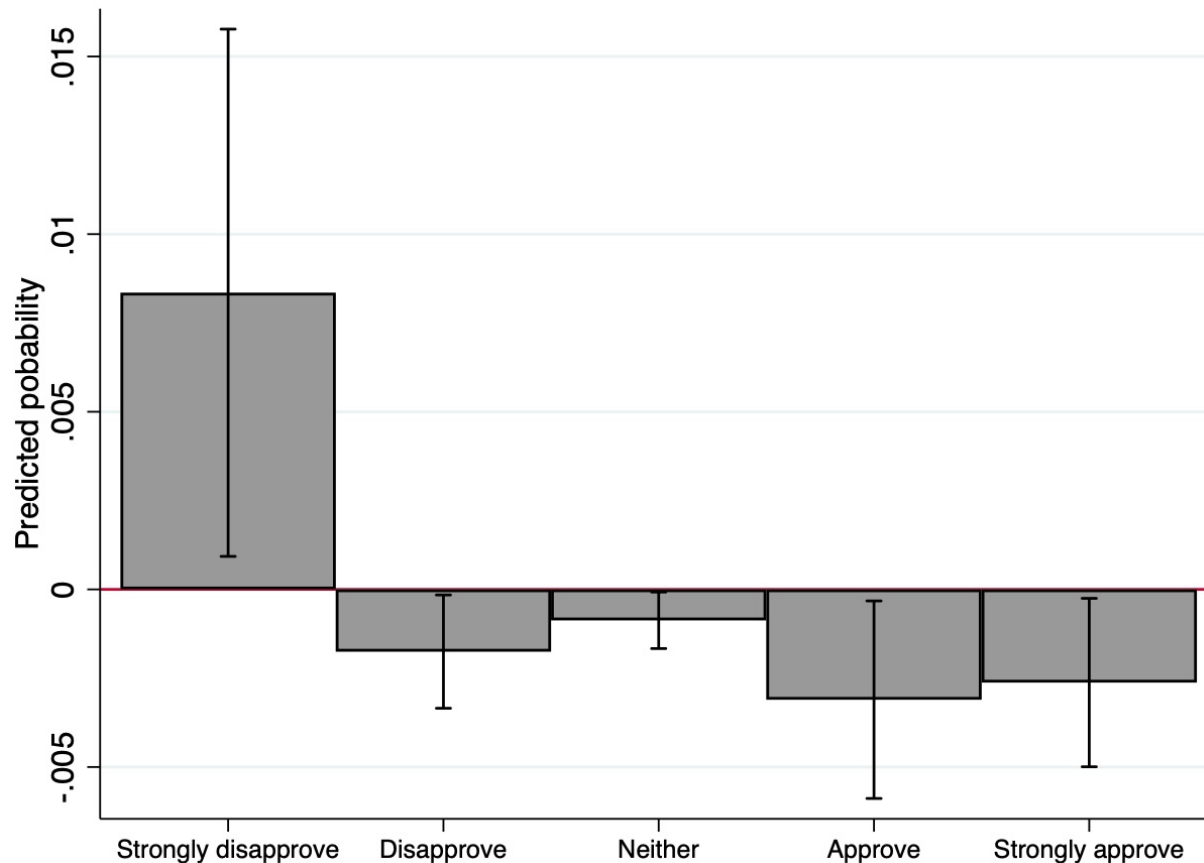


Figure 4: Average marginal effect of violent conflict on attitudes toward military rule in Nigeria

Note: The figure, based on Model 4 in Table 1, visualizes the effect of violent conflict on each category of the dependent variable, which measures Nigerians' attitudes toward military rule. The horizontal axis displays the various levels of support for military rule, while the vertical axis shows the corresponding predicted probabilities. Confidence intervals are set at the 95% level.

To illustrate the magnitude of the effects reported in Table 1, I plotted the average marginal effects for the full model (Model 4) in Figure 4. The figure shows that conflict exposure has a positive effect on only the “Strongly disapprove” category of the dependent variable, while its effect is negative across the remaining four categories. Specifically, a 1-unit increase in the predicted value of conflict exposure increases the probability of strongly disapproving of military rule by 0.84 percentage points. Conversely, it decreases the probability of strongly approving of military rule by 0.26 percentage points.

The negative effect of violent conflict on support for military rule contrasts with the results of a study conducted by Tuki (2024) in the Republic of Niger, which found a positive correlation between conflict exposure and preference for military rule. He suggested that this relationship may stem from the erosion of trust in democratic institutions; as violence intensifies, citizens may come to believe that the military is better equipped than civilian leaders to address the country's security challenges. Furthermore, the military has historically played a prominent role in Nigerien politics, often positioning itself as a “corrective” force—intervening when democratic governments engage in unconstitutional practices, such as attempts to extend presidential term limits. Similarly, in a study of Mali, Bester (2024) argued that widespread violence can generate public frustration with civilian governance. As the military becomes increasingly involved in maintaining order, this presence can gradually translate into overt support for military rule.

A compelling question that arises is: *Why does exposure to violent conflict reduce support for military rule in Nigeria?* One plausible explanation is military overreach. Exposure to violence—such as injury, the death of loved ones, or displacement—can generate strong negative associations with the actors perceived to be responsible. When the military is seen as either failing in its core responsibility to protect civilians or as directly perpetrating violence against them, it loses credibility. This erosion of trust undermines the legitimacy of military institutions. In the Nigerian

context, for example, the military has been involved in several high-profile incidents in which civilians were mistakenly targeted during operations intended to counter terrorism and banditry. These events have raised serious concerns about military conduct and accountability. Although the military often describes such attacks as accidental, their frequency has become deeply troubling.

In January 2025, a military airstrike in Zamfara State killed at least 16 civilians and injured many others after they were mistaken for members of a bandit gang (Ewang 2025; Rukanga 2025). Just weeks earlier, on Christmas Day 2024, another airstrike killed at least 10 civilians and caused numerous injuries in neighboring Sokoto State (Maishanu 2024). A similar incident occurred on September 27, 2024, when a military strike in Kaduna State killed 24 civilians attending a celebration, again due to misidentification as bandits (Ewang 2024). These are only a few among many documented cases in which innocent civilians have lost their lives during military operations (Okoli et al. 2024; Ewang 2024; Human Rights Watch 2023). Additionally, in its fight against terrorist organizations such as the radical Islamist group *Boko Haram*, the Nigerian military has faced significant challenges in earning the trust of local communities. A major obstacle has been the difficulty of distinguishing civilians from insurgents, which has often resulted in indiscriminate or overly aggressive tactics. These challenges have contributed to recurring allegations of human rights abuses committed by the military (Amnesty International 2015; Dietrich 2015).

4. Conclusion

Using survey data from Afrobarometer, this study examined the effect of violent conflict on public attitudes toward military rule in Nigeria. The regression analysis showed that exposure to violent conflict significantly reduced the likelihood of supporting a military government. This finding proved robust across alternative operationalizations of violent conflict. A plausible explanation for this result is military overreach. The Nigerian military's counterterrorism operations—particularly in conflict-affected areas—have frequently resulted in civilian casualties, whether through accidental aerial bombardments or extrajudicial killings. Such incidents likely contribute to perceptions that the military has failed in its fundamental duty to protect civilians and is, in some

cases, directly responsible for civilian harm. As a result, public trust in the military may be eroded, ultimately undermining its legitimacy as a governing institution.

However, the negative effect of violent conflict on support for military rule does not necessarily indicate widespread satisfaction with the democratic government. Instead, it may reflect a deeper sense of disillusionment with both civilian and military leadership, stemming from the perception that neither has effectively addressed Nigeria's ongoing security challenges. For example, Afrobarometer data show that 46% of Nigerians report having no trust at all in the president, and 51% express the same level of distrust toward the National Assembly. In comparison, 29% say they do not trust the army at all, while only 15% express complete distrust in religious leaders. These figures highlight the urgent need for the democratic government to strengthen its capacity to ensure the safety and security of its citizens, thereby restoring public trust in democratic institutions.

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Appendix

Section A:

Table A1: Descriptive Statistics

Variable	Total observations	Mean	Standard deviation	Minimum	Maximum
Military rule ^σ	1586	2.025	1.268	1	5
Conflict (10 km)	1600	43.985	95.362	0	674
Conflict (20 km)	1600	74.32	119.867	0	772
Conflict (30 km)	1600	117.17	153.888	2	824
Conflict (10 km) [2017-2021]	1600	17.375	29.868	0	216
Conflict (10 km) [2020-2021]	1600	10.51	15.656	0	88
Conflict (UCDP) (10 km)	1600	12.155	44.412	0	419
Conflict (GTD) (10 km)	1600	14.97	58.108	0	547
Nighttime light (10 km)	1600	6.501	11.872	0	48.372
Nighttime light (20 km)	1600	4.19	7.502	0	30.541
Nighttime light (30 km)	1600	3.332	5.585	0	22.264
Log Population (10 km)	1600	12.32	1.367	9.577	15.671
Log Population (20 km)	1600	13.457	1.202	10.825	16.307
Log Population (30 km)	1600	14.123	1.1	11.128	16.494
Urban (Ref: Rural)	1600	0.435	0.496	0	1
Trust in Gov't index	1545	2.59	2.248	0	9
Trust army	1590	1.253	0.998	0	3
Corruption index	1521	5.245	2.06	0	9
Lived poverty index	1588	9.455	4.656	0	20
Educational level	1598	4.113	2.239	0	9
Age	1600	34.911	12.71	18	97
Male (Ref: Female)	1600	0.499	0.5	0	1
Distance to border (Km)	1600	162.023	96.216	3.453	389.203

Note: “Ref” indicates the reference category. ^σ indicates the dependent variable.

Table A2: Replicating the results in Table 1 using the conflict measure from UCDP

Dependent variables:				
	Conflict	Military rule		
	1st-stage	2nd-stage		
	(1)	(2)	(3)	(4)
	OLS	IVOProbit	IVOProbit	IVOProbit
Conflict (UCDP) [†]		-0.02*** (0.002)	-0.021*** (0.002)	-0.022*** (0.001)
Distance to border (Km)	-0.037*** (0.007)			
Constant	18.212*** (2.206)			
Intercept 1		-0.269*** (0.033)	-0.554** (0.259)	0.085 (0.411)
Intercept 2		0.165 (0.132)	-0.179 (0.249)	0.371 (0.498)
Intercept 3		0.277* (0.16)	-0.086 (0.255)	0.441 (0.523)
Intercept 4		0.694*** (0.266)	0.249 (0.303)	0.694 (0.617)
Control variables	No	No	Yes	Yes
State Fixed effects	No	No	No	Yes
Observations	1600	1586	1456	1456
R-squared	0.007			
Log pseudolikelihood		-10322.125	-9422.07	-9358.325
Error terms correlation		0.806***	0.869***	0.934***
AIC statistic	16672.28	20662.25	18882.14	18826.65
BIC statistic	16683.03	20710.57	18982.53	19117.24

Note: Robust standard errors are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Model 1, the first-stage regression, is estimated using ordinary least squares (OLS) regression, while Models 2, 3, and 4, the second-stage regressions, are estimated using instrumental variable ordered probit (IVOProbit) regression. [†] denotes the explanatory variable, which is measured using buffers with a radius of 10 km. Control variables include nighttime light, population, urban residence, trust in government, trust in the army, perceived government corruption, index, educational level, age, and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted in Nigeria in 2022.

Table A3: Replicating the results in Table 1 using the conflict measure from GTD

Dependent variables:				
	Conflict	Military rule		
	1st-stage	2nd-stage		
	(1)	(2)	(3)	(4)
	OLS	IVOProbit	IVOProbit	IVOProbit
Conflict (GTD) [†]		-0.016*** (0.002)	-0.016*** (0.001)	-0.017*** (0.001)
Distance to border (Km)	-0.043*** (0.009)			
Constant	21.943*** (2.781)			
Intercept 1		-0.26*** (0.031)	-0.51** (0.232)	0.008 (0.34)
Intercept 2		0.129 (0.137)	-0.186 (0.216)	0.246 (0.422)
Intercept 3		0.229 (0.167)	-0.106 (0.224)	0.304 (0.446)
Intercept 4		0.603** (0.282)	0.184 (0.282)	0.515 (0.537)
Control variables	No	No	Yes	Yes
State Fixed effects	No	No	No	Yes
Observations	1600	1586	1456	1456
R-squared	0.005			
Log pseudolikelihood		-10751.796	-9816.893	-9752.928
Error terms correlation				
AIC statistic	17534.85	21521.59	19671.79	19615.86
BIC statistic	17545.61	21569.91	19772.17	19906.45

Note: Robust standard errors are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Model 1, the first-stage regression, is estimated using ordinary least squares (OLS) regression, while Models 2, 3, and 4, the second-stage regressions, are estimated using instrumental variable ordered probit (IVOProbit) regression. [†] denotes the explanatory variable, which is measured using buffers with a radius of 10 km. Control variables include nighttime light, population, urban residence, trust in government, trust in the army, perceived government corruption, index, educational level, age, and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted in Nigeria in 2022.

Table A4: Replicating the results in Table 1 using total fatalities (ACLED)

Dependent variables:				
	Conflict	Military rule		
	1st-stage	2nd-stage		
	(1)	(2)	(3)	(4)
	OLS	IVOProbit	IVOProbit	IVOProbit
Total fatalities†		-0.001*** (0.00)	-0.002*** (0.00)	-0.002*** (0.00)
Distance to border (Km)	-0.423*** (0.105)			
Constant	273.576*** (30.049)			
Intercept 1		-0.321*** (0.033)	-0.55** (0.218)	-0.068 (0.335)
Intercept 2		0.046 (0.144)	-0.25 (0.204)	0.159 (0.423)
Intercept 3		0.141 (0.176)	-0.176 (0.214)	0.215 (0.449)
Intercept 4		0.494* (0.294)	0.093 (0.28)	0.416 (0.544)
Control variables	No	No	Yes	Yes
State Fixed effects	No	No	No	Yes
Observations	1600	1586	1456	1456
R-squared	0.004			
Log pseudolikelihood		-14527.186	-13287.279	-13222.513
Error terms correlation				
AIC statistic	25161.43	29072.37	26612.56	26555.03
BIC statistic	25172.19	29120.69	26712.94	26845.62

Note: Robust standard errors are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Model 1, the first-stage regression, is estimated using ordinary least squares (OLS) regression, while Models 2, 3, and 4, the second-stage regressions, are estimated using instrumental variable ordered probit (IVOProbit) regression. † denotes the explanatory variable, which is measured using buffers with a radius of 10 km. Control variables include nighttime light, population, urban residence, trust in government, trust in the army, perceived government corruption, index, educational level, age, and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted in Nigeria in 2022.

Table A5: Replicating the results in Table 1 using buffers with a radius of 20 km

Dependent variables:				
	Conflict	Military rule		
	1st-stage	2nd-stage		
	(1)	(2)	(3)	(3)
	OLS	IVOProbit	IVOProbit	IVOProbit
Conflict†		-0.008*** (0.001)	-0.008*** (0.00)	-0.008*** (0.00)
Distance to border (Km)	-0.093*** (0.025)			
Constant	89.365*** (6.165)			
Intercept 1		-0.604*** (0.051)	-0.728*** (0.236)	-0.184 (0.483)
Intercept 2		-0.189 (0.164)	-0.413 (0.259)	0.065 (0.578)
Intercept 3		-0.082 (0.195)	-0.335 (0.273)	0.127 (0.604)
Intercept 4		0.315 (0.309)	-0.054 (0.344)	0.348 (0.701)
Control variables	No	No	Yes	Yes
State Fixed effects	No	No	No	Yes
Observations	1600	1586	1456	1456
Pseudo R²				
R-squared	0.006			
Log pseudolikelihood		-11884.593	-10886.039	-10825.174
Error terms correlation		.828***	0.91***	0.95***
AIC statistic	19851.12	23787.19	21810.08	21760.35
BIC statistic	19861.87	23835.51	21910.46	22050.94

Note: Robust standard errors are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Model 1, the first-stage regression, is estimated using ordinary least squares (OLS) regression, while Models 2, 3, and 4, the second-stage regressions, are estimated using instrumental variable ordered probit (IVOProbit) regression. † denotes the explanatory variable, which is measured using buffers with a radius of 20 km. Control variables include nighttime light, population, urban residence, trust in government, trust in the army, perceived government corruption, index, educational level, age, and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted in Nigeria in 2022.

Table A6: Replicating the results in Table 1 using buffers with a radius of 30 km

Dependent variables:				
	Conflict	Military rule		
	1st-stage	2nd-stage		
	(1)	(2)	(3)	(4)
	OLS	IVOProbit	IVOProbit	IVOProbit
Conflict†		-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)
Distance to border (Km)	-0.165*** (0.036)			
Constant	143.936*** (8.564)			
Intercept 1		-0.681*** (0.077)	-0.554 (0.363)	0.48 (1.004)
Intercept 2		-0.162 (0.168)	-0.119 (0.406)	0.866 (1.129)
Intercept 3		-0.028 (0.192)	-0.011 (0.421)	0.961 (1.161)
Intercept 4		0.466* (0.282)	0.378 (0.482)	1.303 (1.282)
Control variables	No	No	Yes	Yes
State Fixed effects	No	No	No	Yes
Observations	1600	1586	1456	1456
Pseudo R²				
R-squared	0.011			
Log pseudolikelihood		-12272.521	-11245.787	-11184.24
Error terms correlation		.715***	.819***	.877***
AIC statistic	20642.37	24563.04	22529.57	22478.48
BIC statistic	20653.12	24611.36	22629.96	22769.07

Note: Robust standard errors are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Model 1, the first-stage regression, is estimated using ordinary least squares (OLS) regression, while Models 2, 3, and 4, the second-stage regressions, are estimated using instrumental variable ordered probit (IVOProbit) regression. † denotes the explanatory variable, which is measured using buffers with a radius of 30 km. Control variables include nighttime light, population, urban residence, trust in government, trust in the army, perceived government corruption, index, educational level, age, and gender. AIC = Akaike information criterion; BIC = Bayesian information criterion. The regression models are based on data from Round 9 of the Afrobarometer survey conducted in Nigeria in 2022.

Table A7: Replicating the results in Table 2 using the subsample of respondents living at least 50 km from the border

Dependent variables:				
	Conflict	Military rule		
	1st-stage	2nd-stage		
	(1)	(2)	(3)	(4)
	OLS	IVOProbit	IVOProbit	IVOProbit
Conflict†		-0.007*** (0.001)	-0.007*** (0.001)	-0.008*** (0.001)
Distance to border (Km)	-0.177*** (0.022)			
Constant	77.683*** (5.961)			
Intercept 1		-0.37*** (0.056)	-0.952** (0.389)	0.165 (0.726)
Intercept 2		0.251** (0.107)	-0.366 (0.387)	0.703 (0.803)
Intercept 3		0.414*** (0.122)	-0.217 (0.389)	0.84 (0.826)
Intercept 4		0.981*** (0.174)	0.274 (0.402)	1.285 (0.908)
Control variables	No	No	Yes	Yes
State Fixed effects	No	No	No	Yes
Observations	1480	1466	1339	1339
R-squared	0.028			
Log pseudolikelihood		-10688.511	-9735.476	-9677.146
Error terms correlation		0.551***	0.65***	0.753***
AIC statistic	17746.99	21395.02	19508.95	19464.29
BIC statistic	17757.59	21442.63	19607.75	19750.28

Note: Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.10. Model 1, the first-stage regression, is estimated using ordinary least squares (OLS) regression, while Models 2, 3, and 4, the second-stage regressions, are estimated using instrumental variable ordered probit (IVOProbit) regression. † denotes the explanatory variable, which is measured using buffers with a radius of 10 km. Control variables include nighttime light, population, urban residence, trust in government, trust in the army, perceived government corruption, index, educational level, age, and gender. The regression models are based on data from Round 9 of the Afrobarometer survey conducted in Nigeria in 2022.

Table A8: Replicating the results in Table 2 using the subsample of respondents living at least 100 km from the border

Dependent variables:				
	Conflict	Military rule		
	1st-stage	2nd-stage		
	(1)	(2)	(3)	(4)
	OLS	IVOProbit	IVOProbit	IVOProbit
Conflict†		-0.007*** (0.001)	-0.008*** (0.001)	-0.009*** (0.001)
Distance to border (Km)	-0.251*** (0.039)			
Constant	97.071*** (10.808)			
Intercept 1		-0.386*** (0.056)	-0.865* (0.492)	0.043 (0.754)
Intercept 2		0.288*** (0.101)	-0.202 (0.48)	0.617 (0.819)
Intercept 3		0.453*** (0.114)	-0.047 (0.479)	0.751 (0.838)
Intercept 4		1.072*** (0.163)	0.501 (0.481)	1.221 (0.907)
Control variables	No	No	Yes	Yes
State Fixed effects	No	No	No	Yes
Observations	1088	1076	973	973
R-squared	0.042			
Log pseudolikelihood		-7847.217	-7070.439	-7022.594
Error terms correlation		0.503***	0.576***	0.748***
AIC statistic	13026.83	15712.43	14178.88	14147.19
BIC statistic	13036.81	15757.26	14271.6	14396.09

Note: Robust standard errors are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Model 1, the first-stage regression, is estimated using ordinary least squares (OLS) regression, while Models 2, 3, and 4, the second-stage regressions, are estimated using instrumental variable ordered probit (IVOProbit) regression. † denotes the explanatory variable, which is measured using buffers with a radius of 10 km. Control variables include nighttime light, population, urban residence, trust in government, trust in the army, perceived government corruption, index, educational level, age, and gender. The regression models are based on data from Round 9 of the Afrobarometer survey conducted in Nigeria in 2022.

Table A9: Replicating the results in Table 2 using an explanatory variable measuring conflict exposure within the 10 km radius from 2017–2021 (5 years before survey)

Dependent variables:				
	Conflict	Military rule		
	1st-stage	2nd-stage		
	(1)	(2)	(3)	(4)
	OLS	IVOProbit	IVOProbit	IVOProbit
Conflict (2017–2021)†		-0.032*** (0.002)	-0.034*** (0.001)	-0.034*** (0.001)
Distance to border (Km)	-0.02*** (0.006)			
Constant	20.579*** (1.42)			
Intercept 1		-0.579*** (0.044)	-0.703*** (0.166)	-0.343 (0.295)
Intercept 2		-0.203 (0.162)	-0.467*** (0.177)	-0.16 (0.386)
Intercept 3		-0.106 (0.195)	-0.408** (0.195)	-0.115 (0.411)
Intercept 4		0.255 (0.317)	-0.196 (0.281)	0.047 (0.505)
Control variables	No	No	Yes	Yes
State Fixed effects	No	No	No	Yes
Observations	1600	1586	1456	1456
R-squared	0.004			
Log pseudolikelihood		-9679.415	-8856.44	-8794.385
Error terms correlation		0.861***	0.95***	0.974
AIC statistic	15406.86	19376.83	17750.88	17698.77
BIC statistic	15417.62	19425.15	17851.27	17989.36

Note: Robust standard errors are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Model 1, the first-stage regression, is estimated using ordinary least squares (OLS) regression, while Models 2, 3, and 4, the second-stage regressions, are estimated using instrumental variable ordered probit (IVOProbit) regression. † denotes the explanatory variable, which is measured using buffers with a radius of 10 km. Control variables include nighttime light, population, urban residence, trust in government, trust in the army, perceived government corruption, index, educational level, age, and gender. The regression models are based on data from Round 9 of the Afrobarometer survey conducted in Nigeria in 2022.

Table A10: Replicating the results in Table 2 using an explanatory variable measuring conflict exposure within the 10 km radius from 2020–2021 (2 years before survey)

Dependent variables:				
	Conflict	Military rule		
	1st-stage	2nd-stage		
	(1)	(2)	(3)	(4)
	OLS	IVOProbit	IVOProbit	IVOProbit
Conflict (2020–2021)†		-0.065*** (0.002)	-0.064*** (0.001)	-0.064*** (0.001)
Distance to border (Km)	-0.005* (0.003)			
Constant	11.344*** (0.7)			
Intercept 1		-0.694*** (0.029)	-0.691*** (0.044)	-0.625*** (0.055)
Intercept 2		-0.491*** (0.153)	-0.641*** (0.046)	-0.587*** (0.057)
Intercept 3		-0.439** (0.192)	-0.629*** (0.047)	-0.577*** (0.058)
Intercept 4		-0.246 (0.333)	-0.585*** (0.055)	-0.543*** (0.06)
Control variables	No	No	Yes	Yes
State Fixed effects	No	No	No	Yes
Observations	1600	1586	1456	1456
R-squared	0.001			
Log pseudolikelihood		-8651.553	-7920.743	-7859.668
Error terms correlation		0.962***	0.997***	0.999***
AIC statistic	13344.82	17321.1	15879.49	15829.34
BIC statistic	13355.57	17369.43	15979.87	16119.93

Note: Robust standard errors are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Model 1, the first-stage regression, is estimated using ordinary least squares (OLS) regression, while Models 2, 3, and 4, the second-stage regressions, are estimated using instrumental variable ordered probit (IVOProbit) regression. † denotes the explanatory variable, which is measured using buffers with a radius of 10 km. Control variables include nighttime light, population, urban residence, trust in government, trust in the army, perceived government corruption, index, educational level, age, and gender. The regression models are based on data from Round 9 of the Afrobarometer survey conducted in Nigeria in 2022.

Section B:

Below I discuss the control variables included in the regression models. Unless otherwise stated, all variables were derived from the **Afrobarometer survey**. To proxy **economic development**, I use **mean nighttime light intensity**, measured within a 10-kilometer radius of each respondent's dwelling in 2020 (Ghosh et al. 2021).¹⁰ This variable ranges from **0 to 63**, with higher values indicating greater light intensity and, by extension, better economic performance. The **population** variable captures the total number of individuals living within the same 10-kilometer buffer in 2020, based on data from **WorldPop** at the **University of Southampton**.¹¹

Urban residence is a binary variable coded **1** if the respondent resides in an urban center and **0** if in a rural area. To measure **trust in the democratic government**, I constructed an index based on three survey items that ask respondents how much they trust the **president**, **national assembly**, and **courts**. Each item was measured on a four-point ordinal scale from “**0 = Not at all**” to “**3 = A lot.**” I created an **additive index** by summing responses across the three items, resulting in a scale from **0 to 9**, with higher scores indicating greater trust. The index demonstrated strong internal reliability, with a **Cronbach's Alpha** of **0.774**. **Trust in the army** was measured using a single item asking respondents how much trust they have in the military, with responses recorded on a four-point ordinal scale ranging from “**0 = Not at all**” to “**3 = A lot.**” **Perceived corruption in the democratic government** was measured using three items that assess the extent to which respondents believe the president, national assembly, and law courts are involved in corruption. Responses were recorded on a four-point scale ranging from “**0 = None**” to “**3 = All of them.**” These items were combined into an additive index ranging from 0 to 9, with higher scores indicating greater perceived corruption. The index demonstrated strong internal reliability, with a Cronbach's alpha of 0.787.

Following Mattes et al. (2002), poverty was assessed through a lived **poverty index**, constructed from five items asking how often, in the past year, respondents and their families went without basic necessities such as food, clean water, medicine when sick, cooking fuel, and income. Each item was measured on a five-point scale from “**0 = Never**” to “**4 = Always.**” Summing the responses yielded a scale ranging from 0 to 20, with higher scores reflecting greater levels of lived poverty. The index showed high internal consistency, with a Cronbach's alpha of 0.812. **Educational attainment** is measured on a 10-point ordinal scale ranging from “**0 = No formal schooling**” to “**9 = Postgraduate.**” **Gender** is coded as 1 for male and 0 for female, while **age** is measured in years.

¹⁰ To access the raw nighttime light dataset visit: <https://eogdata.mines.edu/products/dmsp/>

¹¹ To access the raw population dataset visit: <https://www.worldpop.org/>

References 2

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