Shaping Anti-Corruption Campaigns in Nigeria*

Youth Populations, Urban Areas and Moderately Educated Citizens Are Important for Anti-Corruption Campaigns

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Peceptions of corruption in the Nigerian presidency vary significantly across demogrpahic groups. Using Afrobarometer survey data and Bayesisan ordinal logistic regression, this study looks at how education, gender, age, and urban versus rural residence influence these perceptions. The results show that urban residents and younger individuals are more likely to perceive high corruption, while rural populations and those with higher education show views that are moderate. These results show the need for targeted anti-corruption campaigns to adress demographic differences and imporve governance and accountability in Nigeria

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*Code and data are available at:https://github.com/fatimahsy/Nigeria_Democracy-

1 Introduction

Corruption is a big challenge to governance and development in Nigeria as a result of its ability to undermine public trust and economic growth. As the United Nations Office on Drugs and Crime (UNODC) stated, "corruption affects the lives of ordinary Nigerian, impeding development and eroding public trust in institutions (United Nations Office on Drugs and Crime (UNODC) 2024). This paper looks into the role of demographic factors-education,gender,age,

and urban versus rural residence-in shaping perceptions of corruption in the Nigerian presidency.

Primarily, this paper is aimed at understanding how different demographic groups perceive corruption in the Nigerian presidency and to identify ways this can help improve anti-corruption campaigns, While existing studies have largely been focused on the institutional dynamics, there seems to be a lack of demographic-specific analysis within the Nigerian context. This paper addresses this by making these demographics the focus. It does this by using nationally representative data from Afrobarometer (Afrobarometer 2023), a leading survey initiative capturing public attitudes on governance, democracy, and corruption across Africa. A Bayesian ordinal logistic regression was used to find patterns in how education, gender, age, and geographic location influence perceptions of corruption.

Our paper shows that there are a lot of disparities in corruption perceptions across demographic groups. Younger respondents and urban residents have higher perceptions of corruption, likely because of higher exposure to investigative media and political discourse. In contrast, rural populations-often reliant on patronage systems- tend to report more neutral views. Education also plays an important role since we find that secondary school graduates have the highest corruption perceptions.

Understanding these demographic differences is important for designing effective anti-corruption campaigns. Making sure outreach efforts are tailored to the unique experiences and perceptions of different demographic groups can increase their effectiveness and increase public trust. For example, youth-focused campaigns that use social media platforms and urban outreach using investigative journalism can engage the people. At the same time, localized, culturally appropriate campaigns in rural areas can address the different needs of these populations. As the UNODC emphasizes, "targeted and effective anti-corruption policies will improve lives of Nigerian citizens" (Afrobarometer 2023).

The remainder of this paper is structured as follows; Section 2 details the data used for this paper, Section 3 introduces the Bayesian ordinal logistic regression model used to study the relationship between our variables of interest. Section 4 presents the findings from the model, detailing how different demographic factors like education and age affect corruption perception in Nigeria. Section 5 examines these results, discussing their implications for anti-corruption policies, weaknesses and next steps. Section A.1 explores the details of the Afrobarometer survey. Section D shows plots for Posterior predictive checks and Diagnostics as well as their analysis. Section A.1 details the survey methodology used in the Afrobarometer data and Section A.2 addresses very important ethical principles and the ethical challenges of surveying sensitive topics like corruption.@sec-Data-Driven-Narrative-appendix introduces a narrative example, 'Amina's Story,' to humanize the data by showing how demographic factors like age, education, and urban residency shape individual perceptions of corruption, while emphasizing the ethical importance of considering the lived experiences behind the data.

2 Data

2.1 Measurement

For this analysis, i use the Afrobarometer Round 9, Nigeria survey. Afrobarometer conducts surveys that are nationally representative across African nations to capture public perceptions on topics like governance, democracy, and economic issues. The Nigerian Round 9 survey dataset contains responses from 1,556 people and shows the diverse demographic statistics across gender, region, and residence type(urban or rural). The data is freely available on the Afrobarometer website(Afrobarometer 2023) and was collected through a multi-stage, stratified sampling method. This is to ensure representativeness and enables analysis of different demographics and socioeconomic indicators.

Our primary measurement task is to capture public opinion towards economic, political and socioeconomic issues and translate it into actionable lintel. The Afrobarometer survey translates these real world perceptions into quantifiable data using survey instruments.The process begins with identifying relevant phenomena in the Nigerian socio-political and economic context, such as public attitudes toward democracy, demand for governance accountability, and perceived economic conditions. These phenomena are operationalized into survey questions that are clear, culturally sensitive, and tailored to elicit meaningful responses (Afrobarometer 2022a).

For example:

- Perceptions of Democracy: A phenomenon such as the demand for democracy is operationalized by questions asking respondents whether they prefer democracy over other forms of governance, and whether they believe Nigeria is a democratic nation. These questions are grounded in observable public discourse, historical trends, and policy outcomes.
- Economic Prosperity: Attitudes toward economic conditions are measured by asking individuals to rate the current state of the economy and their own living standards. These subjective evaluations stem from tangible experiences like inflation, unemployment, or changes in public service delivery.

Each survey question acts as a data proxy for these real-world dynamics, reducing them to quantifiable variables while keeping their conceptual integrity.This dataset shows a unique moment in Nigeria's socio-political landscape, showing how citizens perceive democracy and governance in the context of ongoing economic and political challenges. Alternative datasets, such as Nigeria's national statistics or World Bank survey data, could provide economic indicators but do not have the granularity of Afrobarometer's public opinion data.

The data for this study was downloaded, cleaned, analyzed, modeled, and visualized using R (R Core Team 2023), a statistical programming language.(Afrobarometer 2023) served as the primary data source, providing importantsurvey data for analysis.***Telling Stories with***

Data (Alexander 2023) was referenced for its methodologies. The following packages were used:

- **modelsummary** (Arel-Bundock 2022): Used to create well-formatted regression tables and summaries.
- **rstanarm** (Team 2021): Facilitated Bayesian regression modeling using the Stan backend.
- **dplyr** (Wickham et al. 2023): Streamlined data manipulation, transformation, and summarization processes.
- **here** (Müller 2020): Simplified the organization of file paths, improving project reproducibility.
- **arrow** (Richardson et al. 2024): Enabled efficient handling of large datasets with fast reading and writing capabilities.
- **bayesplot** (Gelman, Gabry, et al. 2021): Assisted in producing diagnostic checks and posterior predictive visualizations for Bayesian models.
- **ggplot2** (Wickham 2016): Provided extensive tools for creating clear and impactful visualizations.
- **patchwork** (Pedersen 2024): Combined multiple plots into cohesive, professional visuals.
- **knitr** (Xie 2021): Enabled dynamic report generation, integrating code, output, and text seamlessly.
- **kableExtra** (Zhu 2024): Enhanced table styling and formatting for clean, professional presentations.
- **ggalt** (Rudis, Bolker, and Schulz 2017): Allowed the creation of specialized plots, enhancing the depth of data visualizations.
- **haven** (Wickham, Miller, and Smith 2023): Facilitated the import of `.sav` survey data from the Afrobarometer.
- **broom.mixed** (Bolker and Robinson 2024): Streamlined the extraction and tidying of results from mixed models for easy analysis and visualization.
- *Telling Stories with Data* (Alexander 2023): This book was referenced for its code and methodologies.

2.2 Cleaned Data Overview

Table 1: Preview of the Cleaned Dataset

corruption_presidency	education	gender	age_group	urban_rural	region
Some Corruption	Some university	Female	25-34	Urban Residents	634
Some Corruption	Primary school completed	Male	45-54	Urban Residents	634
High Corruption	Some university	Male	18-24	Urban Residents	634
Some Corruption	Some secondary schooling	Male	35-44	Urban Residents	634
Some Corruption	University completed	Male	25-34	Urban Residents	634

Table 1 represents the first six cleaned rows of the dataset, showing the important variables used in the analysis. The variables were constructed from specific survey questions in the Afrobarometer Round 9 Nigeria Survey (Afrobarometer 2023), which captures several socioeconomic sentiments within the country.The column `corruption_presidency` captures perceptions of corruption within the office of the presidency, derived from responses to the question, *"How many of the following people do you think are involved in corruption, or haven't you heard enough about them to say: the president and officials in his office?"* The variable education reflects respondents' highest level of education completed, gathered from the question, *"What is the highest level of education you have completed?"* The gender variable indicates the respondent's gender, collected through direct demographic inquiry. The column age_group categorizes respondents into age brackets based on the question,* "How old are you?"* The urban_rural variable distinguishes between urban and rural respondents, as recorded by interviewers based on the primary sampling unit (PSU) during data collection (Afrobarometer 2022b). Lastly, region specifies the geographical region of each respondent, identified using a unique code for Nigerian states. This table not only demonstrates the diversity of the dataset but also highlights the breadth of demographic and governance-related variables included for analysis.

Table 2: Detailed Summary Statistics of the Cleaned Dataset (Transposed)

Statistic	Value
Most Frequent Age Group	25-34
Urban Percentage	43.38%
Male Percentage	49.68%
Corruption Counts	None: 61 Some: 574 High: 593 All: 328
Education Counts	Primary: 203 Secondary: 173 University: 102 Postgraduate:

The cleaned dataset used in this study is summarised in Table 2, which provides important statistics to provide an overview of the dataset's structure and characteristics. The most frequent age group among respondents is identified, representing the predominant demographic in terms of age. The table also highlights the urban and male percentages, which indicate the proportion of urban residents (43.38%) and male respondents (49.68%) in the sample.

Further, the table breaks down the perceptions of corruption into four categories—"None," "Some," "High," and "All"—with counts for each, offering information into respondents' views on corruption in the presidency. Additionally, the table details the distribution of respondents across education levels, including categories such as "Primary," "Secondary," "University," and

"Postgraduate." Together, these summary statistics provide a very detailed snapshot of the dataset, enabling a clear understanding of its demographic and categorical variables.
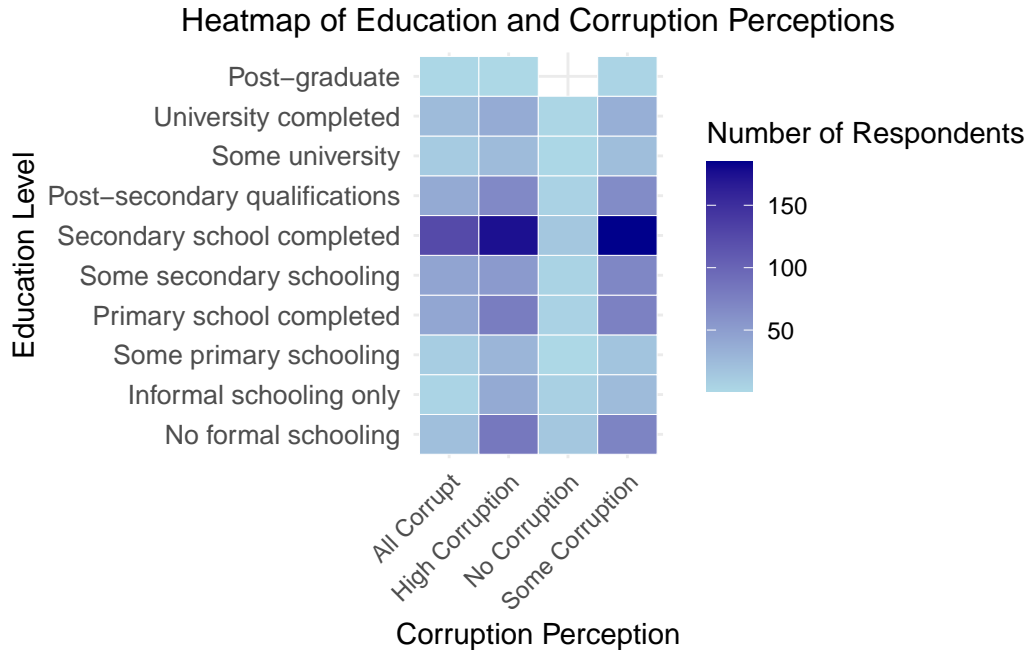
2.3 Corruption Perceptions Vs Variables of Interest

Figure 1: Relationship between Education Levels and corruption percetpions in Nigeria

This heatmap in Figure 1 shows the relationship between respondents' education levels and their perceptions of corruption in Nigeria. The data reflects responses to the question: *What is your highest level of education?.*The x-axis represents corruption perception categories (All Corrupt, High Corruption, No Corruption, and Some Corruption), while the y-axis represents education levels, ranging from No Formal Schooling to Post-graduate. The intensity of the color reflects the number of respondents, with darker shades indicating higher counts.

The heatmap shows that respondents who completed secondary school or some secondary schooling dominate the High Corruption and Some Corruption categories. Respondents with higher education levels (university and post-graduate) are distributed more evenly across the corruption perception categories, with fewer concentrated in any specific category. Conversely, respondents with no formal schooling or only informal education are sparsely represented across all categories.There is a notable concentration of corruption perceptions among respondents with mid-level education (secondary schooling), while those with higher education tend to have more varied perceptions. These findings suggest a potential link between educational

attainment and experiences or attitudes toward corruption, particularly among those with secondary-level education.
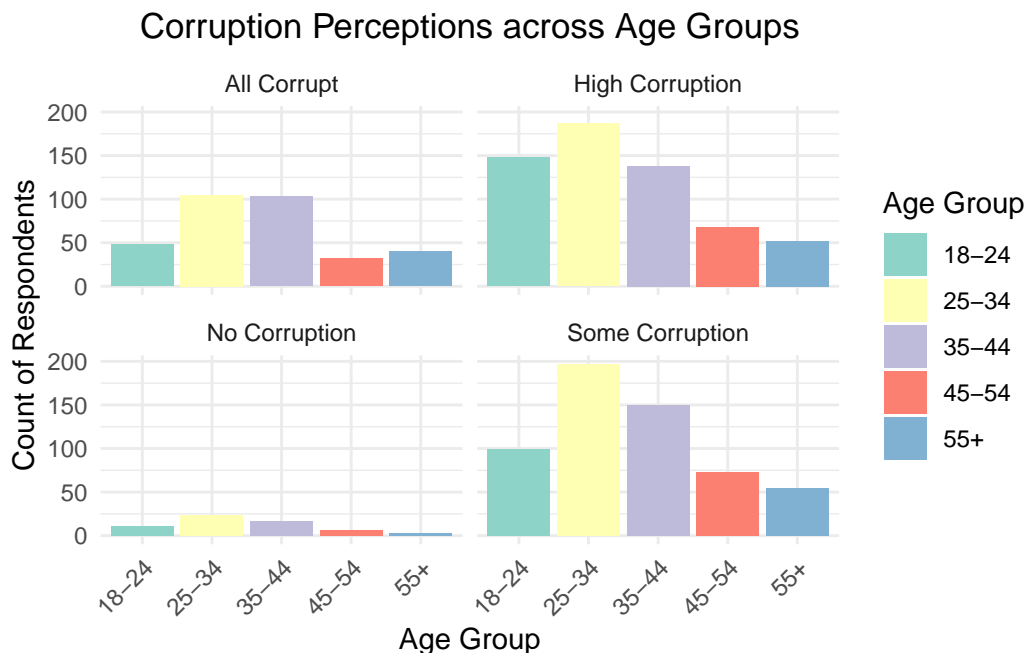

Figure 2: Age Group Vs. Corruption Perception. This faceted bar chart plots the relationship between the age group of respondents and their different corruption perception levels in Nigeria.

Figure 2 shows the relationship between respondents' age group which was obtained by asking the respondent *How old are you?* and their perceptions of corruption in Nigeria. Each panel corresponds to one of four corruption perception levels. Within each panel, the bars represent the count of respondent across five age groups (18-24, 25-34, 35-44, 45-54, and 55+), enabling a clear comparison of how perceptions vary by age.

The 25–34 and 35–44 age groups have the highest counts in the High Corruption and Some Corruption categories, suggesting that middle-aged respondents are more likely to perceive corruption as significant. In contrast, younger respondents (18–24) and older respondents (55+) report lower levels of corruption perception in these categories.In the All Corrupt category, the 25–34, 35–44, and 55+ age groups dominate, while the 18–24 and 45–54 groups have lower counts. The No Corruption category has low counts across all age groups, indicating that very few respondents, regardless of age, perceive the absence of corruption.

These results indicate that middle-aged respondents (25–44) are the most likely to report high levels of corruption perception, while younger and older groups report less. The consistently low counts in the No Corruption category reflect a widespread belief that corruption is a persistent issue in Nigeria.
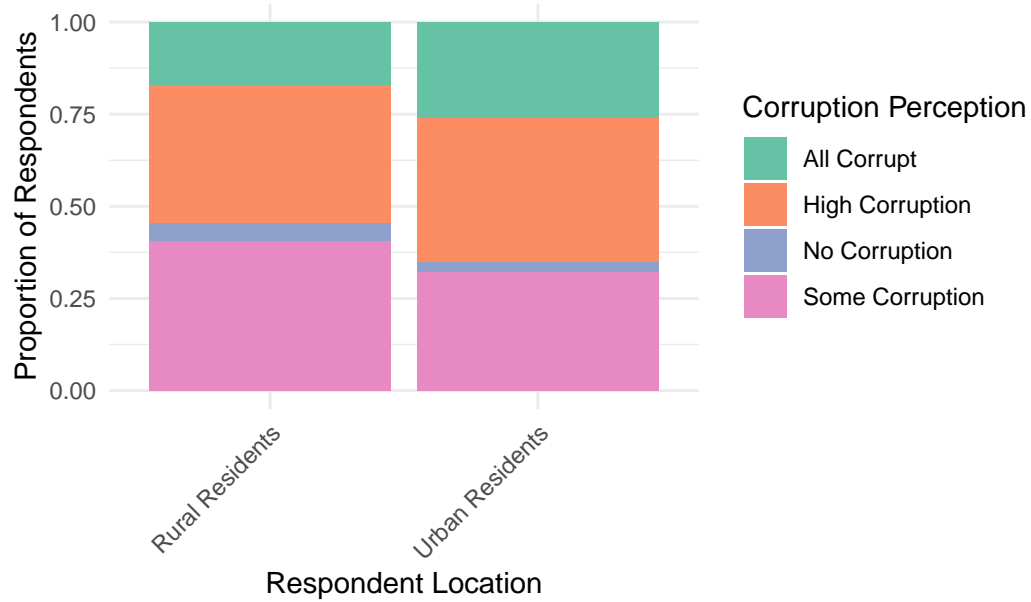
Figure 3: Rural/Urban Vs. Corruption Perception. This stacked bar chart visualises the relationship between respondents' corruption perceptions and weather they live in rural or urban areas in Nigeria.

The relationship between respondents' residential location (rural vs. urban) and their perceptions of corruption is shown in Figure 3 Each bar represents the proportion of respondents within rural and urban groups who hold different corruption perceptions.The chart shows that rural and urban respondents share similar patterns of corruption perception. The majority of respondents in both groups fall under the "Some Corruption" and "High Corruption" categories, with "Some Corruption" being slightly more prevalent. The "All Corrupt" category is the third most common perception in both groups, while the "No Corruption" category is consistently the least represented.

Residential location does not significantly influence corruption perceptions, as rural and urban respondents report similar distribution patterns across all categories. The results suggest that perceptions of corruption are pervasive and relatively consistent across geographic locations.
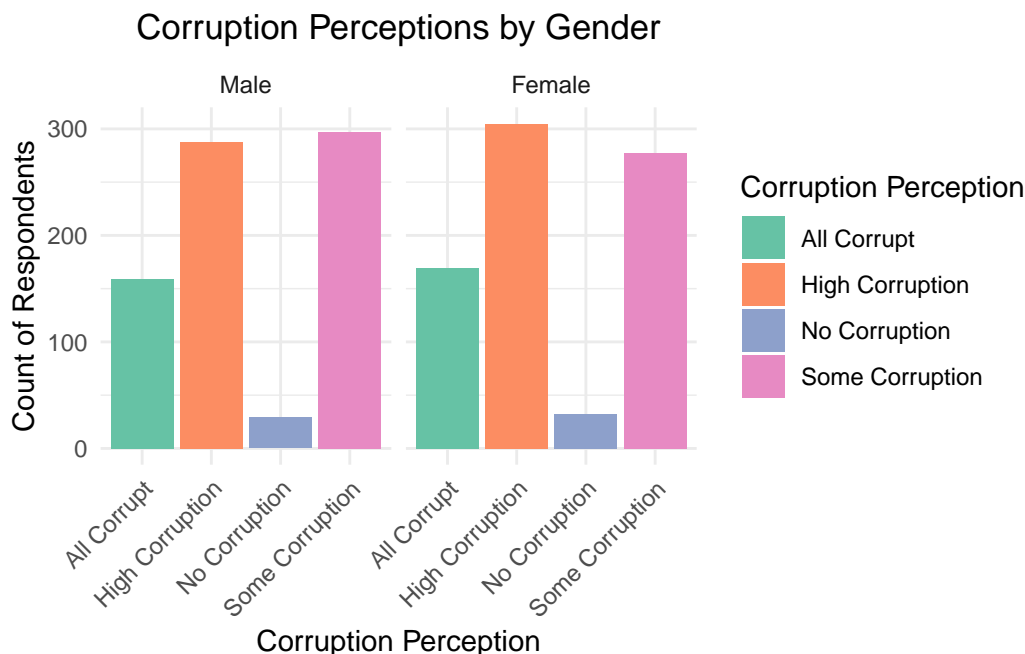
Figure 4: Gender Vs corruption perceptions. This faceted bar chart shows the relationship between a respondents' gender and how they perceive corruption within the presidency in Nigeria.

Figure 4 shows the relationship between respondents' gender (male and female) and their perceptions of corruption. Each panel represents one gender, displaying the count of respondents across four corruption perception categories: All Corrupt, High Corruption, Some Corruption, and No Corruption.

The chart shows that both male and female respondents share similar patterns of corruption perception. The High Corruption and Some Corruption categories have the highest counts for both genders, indicating these are the most commonly held views. The All Corrupt category

has fewer respondents, while the No Corruption category consistently has the lowest counts for both genders.

3 Model

3.1 Model set-up

A Bayesian ordinal logistic regression model is used to estimate the relationship between various demographic factors and perceptions of corruption in the presidency. Ordinal logistic regression is a statistical technique used for ordered categorical outcomes to predict the cumulative probability of being in a particular category or below, given a set of predictor variables.

My model includes four independent demographic variables: `education`, `gender`, `urban_rural`, and `age_group`. The dependent variable is `corruption_presidency`, which has four ordered categories: "None," "Some," "Most," and "All."

The ordinal logistic regression model I used is:

$$\log\left(\frac{P(y_i \leq j)}{P(y_i > j)}\right) = \alpha_j - (\beta_1 \times \text{education} + \beta_2 \times \text{gender} + \beta_3 \times \text{urban rural} + \beta_4 \times \text{age group})$$

(1)

$$\beta_1 \sim \text{Normal}(0, 2.5)$$
$$\beta_2 \sim \text{Normal}(0, 2.5)$$
$$\beta_3 \sim \text{Normal}(0, 2.5)$$
$$\beta_4 \sim \text{Normal}(0, 2.5)$$
$$\alpha_j \sim \text{Normal}(0, 2.5) \quad \text{for } j = 1, 2, 3$$
$$\pi_{ij} \sim \text{Dirichlet}(\alpha = 1)$$

where:

- y_i represents the ordinal outcome for respondent i, indicating their perception of corruption in the presidency.

- $P(y_i \leq j)$ is the cumulative probability of respondent i falling into category j or below.

- α_j are the threshold parameters that define the boundaries between the corruption categories.

- $\beta_1, \beta_2, \beta_3, \beta_4$ are the coefficients corresponding to the predictors:

    - β_1: Education level of the respondent.
    - β_2: Gender of the respondent (male or female).
    - β_3: Urban or rural location of the respondent.

– β_4: Age group of the respondent.

- π_{ij} is the probability that respondent i falls into corruption category j.

In this model, the priors reflect a belief that the predictors explain about 20% of the variability in the outcome, as defined by the $R^2(0.2)$ prior. The Normal priors with a mean of 0 and standard deviation of 2.5 for the coefficients and threshold parameters are relatively weakly informative, ensuring the data have a significant role in determining the posterior distributions.

The threshold parameters (α_j) separate the ordered categories of the outcome variable, while the Dirichlet prior for π_{ij} assumes no strong prior preference for any specific corruption category.The use of these priors provides flexibility for the model while preventing overfitting. The posterior distributions for the coefficients and thresholds, along with diagnostic checks for model convergence and predictive accuracy, can be found in the Appendix.

3.1.1 Model Assumptions

The model relies on the following assumptions:

- Proportional Odds: The relationship between the predictors and the log-odds of being in a higher corruption category is constant across thresholds.
- Ordinal Outcomes: The response categories are ordered, but the distances between them are not quantitatively defined.
- Independence of observations: Responses from different individuals are assumed to be independent.

3.2 Model Justification

The Bayesian approach was chosen because of its flexibility in incorporating prior beliefs and its ability to provide real quantification for uncertainty for parameter estimates. An ordinal logistic regression model is appropriate because the outcome variable (perceived corruption) is inherently ordered.

The predictors-education, gender, urban/rural location, and age group- were selected based on their theoretical relevance to perceptions of governmental corruption in Nigeria, as discussed in the data section. For example, urban and rural individuals may influence exposure to governance systems, while education might shape perceptions of systemic corruption.

The modeling decisions align closely with the structure and characteristics of the dataset to ensure interpretability and relevance. Age was included as a categorical variable reflecting predefined groups, allowing the model to capture non-linear relationships between age and perceptions of corruption. Education was treated as a categorical variable to account for differences across distinct milestones, such as "Primary school completed" and "Post-graduate

qualifications." Gender was modeled as a binary variable ("Male" or "Female") to reflect societal influences on corruption perceptions. Urban versus rural context was included as a binary variable to capture potential differences in exposure to governance and information access. While the dataset includes regional information, province effects were excluded to maintain focus on demographic factors and simplify the model. Finally, the ordinal logistic regression framework was chosen to respect the ordered nature of the outcome variable ("None," "Some," "Most," "All") without assuming equal distances between categories. These decisions ensure the model is both consistent with the data and well-suited to addressing the research question.

4 Results

4.1 Corruption Perceptions Model

Table 3: Detailed Summary of the Bayesian Model with Credible Intervals

	Fixed Effects			
Term	Estimate	Std. Error	2.5% CI	97.5% CI
educationInformal schooling only	-0.008	0.248	-0.422	0.396
educationSome primary schooling	0.427	0.249	0.013	0.849
educationPrimary school completed	0.309	0.175	0.006	0.594
educationSome secondary schooling	0.315	0.194	-0.004	0.636
educationSecondary school completed	0.353	0.168	0.076	0.616
educationPost-secondary qualifications	0.294	0.198	-0.021	0.616
educationSome university	0.160	0.269	-0.280	0.607
educationUniversity completed	0.342	0.230	-0.063	0.709
educationPost-graduate	-0.178	0.738	-1.465	1.055
genderFemale	0.115	0.096	-0.039	0.272
urban_ruralRural	-0.397	0.099	-0.561	-0.228
age_group25-34	-0.127	0.126	-0.339	0.086
age_group35-44	0.016	0.135	-0.212	0.238
age_group45-54	-0.118	0.166	-0.401	0.163
age_group55+	0.174	0.185	-0.126	0.471
None|Some	-3.168	0.233	-3.551	-2.795
Some|Most	-0.317	0.206	-0.649	0.013
Most|All	1.408	0.209	1.074	1.741

The analysis revealed trends in corruption perceptions in different demographics. Our results are summarized in Table 3. This presents the estimated coefficients and standard errors for each predictor included in the model. The dependent variable is the perception of corruption in the presidency, categorized into ordered levels. The table includes predictors such as education level, gender, urban or rural location, and agre group, which are modeled to explain variations in corruption perceptions. Each predictor's coefficient represents its effect on the log odds of perceiving corruption in the presidency at a specific level relative to lower levels, holding other variables constant.

Higher education levels(e.g., university or post-graduate qualifications) are associated with positive effects on corruption perceptions, indicating a greater likelihood of perceived higher levels of corruption. Being female shows a small positive association with higher corruption perceptions. Residing in rural areas is negatively associated with corruption perceptions, suggesting lower perceptions of corruption compared to urban counterparts. Age groups show minimal variation in their association with corruption perceptions, with no significant deviations observed among different age brackets.
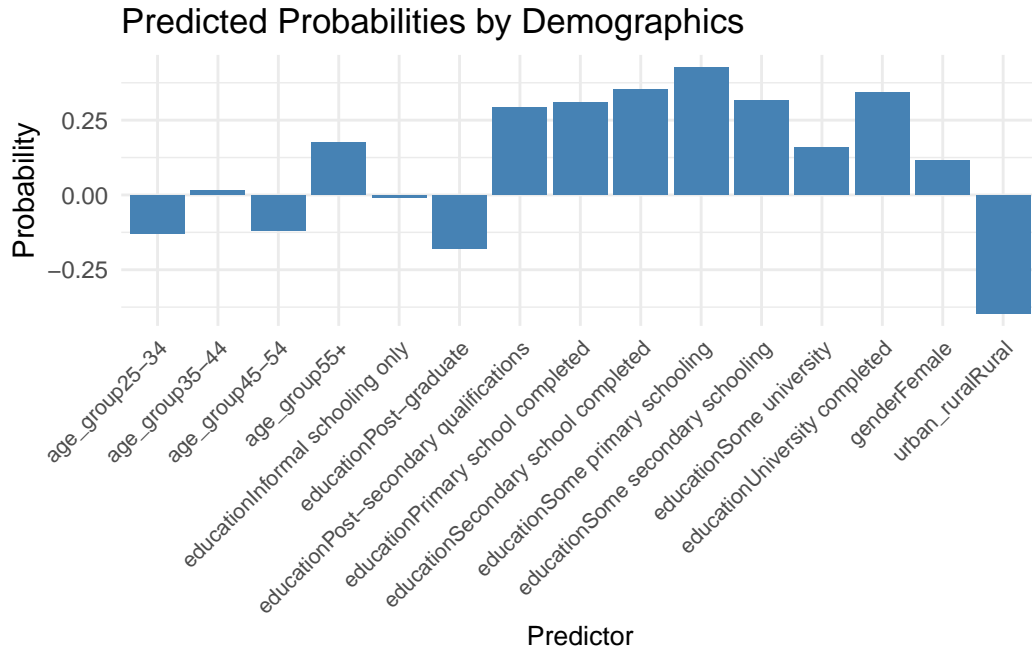
4.2 Predicted Probabilities

Figure 5: Predicted probabilities of high corruption perceptions by key predictors.

Figure 5 illustrates the predicted probabilities derived from the Bayesian ordinal logistic regression model for different demographic predictors influencing corruption perceptions in Nigeria.

Each bar represents the estimated impact of a specific predictor on the likelihood of perceiving higher corruption levels in the presidency.

Higher education levels consistently show positive probabilities, indicating that individuals with higher education levels are more likely to perceive higher corruption levels. Living in rural areas has a significantly negative probability, suggesting that rural residents are less likely to perceive high corruption compared to urban residents. Gender shows a moderate positive probability, with females slightly more likely to perceive higher corruption levels than males. There seems to be minimal variation observed across age groups, suggesting that age does not substantially influence perceptions of corruption.

The results show that higher levels of education, particularly university completion and post-secondary qualifications, are associated with greater perceptions of corruption in the presidency. Urban residents demonstrate significantly higher perceived corruption levels compared to rural residents. Gender differences reveal that female respondents show slightly higher corruption perceptions, while age groups show minimal variation. These findings are shown in the regression estimates and predicted probabilities, as visualized in Figure 5 and summarized in Table 3.

5 Discussion

This paper looks into the demographic disparities of corruption perception in the Nigerian presidency, using survey data to examine variables like education, gender, age and urban versus rural residence. By looking at these factors, the study aims to inform targeted anti-corruption campaigns and policy making. The Bayesian modeling approach helps us understand the relationship between corruption perceptions and these demographic variables.

5.1 Tareting Education Levels in Anti-Corruption Campaigns

The relationship between education and corruption perceptions shows that respondents with secondary school education are the most likely to perceive high levels of corruption in the presidency. This supports broader research showing that moderate levels of education are linked to increased political awareness and accountability demands, as individuals in this group are better equipped to identify systemic corruption but may lack the structural access to address it effectively (Transparency International 2019). Individuals with higher education, such as university graduates, report more moderate corruption perceptions, this might largely be because of their exposure to diverse viewpoints and greater access to institutional frameworks that allow for political skepticism. These suggest that anti-corruption campaigns targeting this moderately educated demographic should focus on actionable reforms and accountability mechanisms to harness their heightened awareness productively (U4 Anti-Corruption Helpdesk 2023).

5.2 Urban-Rural Dynamics in Perception

Urban respondents are somewhat more likely than their rural counterparts to perceive high corruption in the presidency. This is consistent with findings that urban populations have greater access to investigative reporting and public discourse on corruption, which can amplify awareness and perceptions (U4 Anti-Corruption Helpdesk 2023). On the other hand, rural respondents, who may rely on localized patronage networks for essential services, often exhibit more neutral or unclear perceptions of corruption, influenced by limited media access and dependency on these informal systems. Campaigns should focus on leveraging urban platforms like social media, community-based programs, and public dialogues to engage important urban audiences, while also expanding rural outreach through local radio, grassroots organizations, and educational interventions tailored to these settings.

5.3 The Role of Age, Youth & Gender Engagement

Younger respondents, particularly those aged 25–34, consistently report higher perceptions of corruption compared to older age groups. This aligns with existing research that highlights younger demographics as more vocal in their demands for systemic change in a country like Nigeria, where over 60% of the population is under 25 (United Nations Population Fund 2023), targeted anti-corruption initiatives that harness youth energy are important. These efforts should include digital campaigns on platforms frequently used by younger audiences, interactive town hall discussions, and youth-led advocacy initiatives that focus on transparency and accountability. Importantly, such campaigns need to have clear pathways for action, making it easy for youth to channel their frustration into productive engagement with governance structures.

While gender differences in corruption perceptions were less pronounced in our paper, prior research shows that women often experience corruption indirectly, particularly in accessing healthcare or education systems (Organization for Security and Co-operation in Europe 2021). This shows the need for anti-corruption campaigns that address systemic barriers disproportionately impacting women, emphasizing institutional reforms in sectors that are important to gender equity. Moreover, trust in institutions plays an important role in shaping perceptions. Corruption scandals and perceived impunity have a way of eroding trust, particularly in urban areas where political engagement is higher(Armah-Attoh, Gyimah-Boadi, and Chikwanha 2007). Restoring institutional credibility through transparency and consistent enforcement of anti-corruption measures can increase the effectiveness of campaigns targeting both genders.

5.4 Policy Implications

This paper is focused on looking at trends in the corruption perception between different demographics and seeing how these differences can be used to maximize anti corruption campaigns and policy in Nigeria.From this paper, we find different actionable strategies for improving the

effectiveness of anti-corruption campaigns in Nigeria. First, targeting rural and urban populations differently might be effective. Urban residents, who have greater access to investigative media and public debates, are more likely to perceive high corruption. Campaigns in urban areas should therefore focus on digital platforms like social media and mobile apps, as well as partnerships with investigative journalists and public accountability platforms to engage this group effectively. In rural areas, where reliance on patronage systems and limited media access shape perceptions, grassroots communication strategies like community radio, local town halls, and collaborations with trusted community leaders are better suited to disseminate anti-corruption messaging.

Education also emerges as an important determinant of corruption perceptions. Secondary school graduates exhibit the highest levels of awareness, this suggests that civic education campaigns should focus on this demographic to harness their increased engagement. Integrating anti-corruption education into school curricula could early awareness and long-term attitudinal changes.Youth engagement is very important, given that younger age groups, particularly those aged 25–34, report the highest levels of dissatisfaction with corruption. Social media campaigns tailored to platforms popular with youth, together with interactive town hall discussions and youth-led grassroots initiatives, could channel this demographic's energy into organized anti-corruption efforts.

Lastly, rebuilding public trust in institutions should be a priority. Transparent hiring practices, visible enforcement of anti-corruption laws, and strengthened whistle blower protections are important steps to showing institutional accountability. Localized outreach through community leaders can also help fix the trust divide, particularly in rural settings. Policymakers should put these findings into a data-driven framework so they can adapt strategies based on demographic trends and feedback.

5.5 Weaknesses and next steps

While this paper tells us a lot about the demographic distributions of corruption perception about the presidency in Nigeria, there are a few limitations that have to be considered. The survey data relies on self-reported perception, which can be influenced by social desirability bias which refers to the situation where respondents' endorse more favorable responses in order to enhance their own self-presentation(Tricia Gower 2022).For example, high-profile corruption scandals or electoral promises happening close to survey periods may distort responses. The data does not account for regional differences within these urban rural classifications, which could change the understanding of corruption perceptions further.The last limitation is with the bayesian model, because while the Bayesian model accounts for uncertainty, it does not address potential unobserved variables, like political affiliations or socioeconomic status, which may affect the relationships we say.

Future research should look more into longitudinal trends in corruption perceptions to look at how demographic factors evolve over time. This could be achieve through tracking respondents

across electoral cycles or policy interventions to observe shifts in attitudes. Additionally, looking more into regional subcategories could show us some localized patterns, particularly in states that have different governing structures and resource allocation systems. Expanding the dataset to include qualitative information from interviews and focus groups would also give more information about how demographic characteristics relate to peoples' lived corruption experiences.

Appendix

A Surveys, Sampling, and Observational Data

A.1 Aforbarometer Methodology Overview and Evaluation

A.1.1 Overview

Afrobarometer is a pan-African, non-partisan survey research network established to measure public attitudes on democracy, governance, economic reform, civil society, and quality of like in Africa. It relies predominantly on in-person interviews using a standard questionnaire. The project covers up to 40 countries in Africa. The information collected is intended to be used by various parties including policymakers, activists,teachers and scholars. The surveys are conducted using a standardized questionnaire tailored to specific countries through a process called "indigenization", ensuring relevance to local contexts while keeping comparability across nations (Afrobarometer 2022b).

A.1.2 Population and sampling frame

The Afrobarometer surveys target all citizens of voting age, typically 18 and above, excluding individuals living in institutions such as prisons, military barracks, or hospitals. The sampling frame is based on the most recent official national census. When census data is outdated, population estimates or projections are used to ensure relevance. The surveys employ a clustered, stratified, multi-stage probability sample design, where:

- Clustered sampling groups respondents geographically to reduce costs and logistical complexity.

- Stratified sampling divides the population into subgroups (e.g., urban/rural or regions) to ensure proportional representation.

- Multi-stage sampling involves multiple rounds of random selection, narrowing down from regions to individual households and respondents.

A.1.3 Respondent Recruitment

Afrobarometer follows strict protocols to ensure randomness and gender balance during respondent selection. Interviewers alternate genders with each new interview, starting each day with the gender opposite to the last interview conducted the previous day. If no eligible respondent of the next household. Interviews are conducted only after securing informed consent from the respondents, making sure to keep up with ethical guidelines to ensure respect and confidentiality (Afrobarometer 2022b).

A.1.4 Smpling Approach

The Probability Proportional to Population Size (PPPS) sampling method makes sure that regions with larger populations have a higher chance of being selected. In urban areas, the sampling process typically has four stages: selection of Primary Sampling Units (PSUs) based on population size, random selection of Enumeration Areas (EAs) within PSUs, systemic selection of households within each EA, random selection of respondents within household (Afrobarometer 2022b). In rural areas, an additional stage may be introduced to make sure representativeness across dispersed populations. By using PPPS and randomization at every stage, Afrobarometer minimizes biases and makes sure data is collected efficiently (Afrobarometer 2022b).

A.1.5 Strengths and Limitations

Strengths:

- Random Selection: Ensures every adult citizen has an equal chance of being selected, enhancing representativeness.

- Proportional Sampling: PPPS ensures larger and more populous regions are adequately represented.

- Localized Surveys: Conducted in local languages to ensure accessibility and reduce mis-interpretation of questions.

Limitations:

- Institutional Exclusion: Citizens in prisons, military barracks, and similar institutions are excluded, potentially overlooking significant perspectives.

- Conflict Zones: Areas affected by conflict or logistical challenges may be excluded, limiting geographic coverage.

- Africa-Wide Generalization: While Afrobarometer provides national-level information, its findings cannot be generalized to the entire continent due to contextual variations.

A.2 Ethical considerations

A.2.1 Overview of Afrobarometer's Ethical Framework

Afrobarometer adheres to ethical standards to ensure the protection and dignity of survey respondents. Here are the important components of their ethical framework:

- **Informed Consent**: Respondents are provided with detailed information about the survey's purpose, topics, and their rights before participation. Verbal consent is obtained to account for literacy variations across surveyed populations (Afrobarometer 2022b).
- **Confidentiality and Anonymity**: Personal identifiers are removed during data processing, and data are stored securely to maintain respondent privacy.
- **Cultural Sensitivity**: Questionnaires are carefully pre-tested and translated into local languages, ensuring they are culturally appropriate and easily understood.

These practices are aligned with ethical principles in social science research, including those outlined by the World Association for Public Opinion Research (World Association for Public Opinion Research (WAPOR) 2018).

A.2.2 Ethical Challenges in Corruption Perception Surveys

Researching perceptions of corruption has unique ethical challenges because of the sensitive and sometimes dangerous nature of corruption:

- **Risks to Respondents**: Respondents may fear repercussions for expressing negative views about governance. Afrobarometer mitigates this risk by emphasizing anonymity and employing well-trained enumerators who follow strict protocols (Afrobarometer 2022b).
- **Power Dynamics**: Interviewers may inadvertently influence responses due to perceived power imbalances. Afrobarometer addresses this by alternating gender in interviews and training enumerators to minimize bias.

A.2.3 Sampling and Recruitment Ethics

Afrobarometer's methodology includes a very detailed sampling framework designed to enhance inclusivity and fairness. However, there are still some ethical concerns:

- **Exclusion of Institutional Populations**: Individuals in prisons, military barracks, and similar institutions are excluded, potentially omitting perspectives from disenfranchised groups (Afrobarometer 2022b).
- **Gender Quotas**: The enforcement of equal gender representation ensures that women's voices are equally captured, addressing historical disparities in research participation (Afrobarometer 2022b).
- **Regional and Security Constraints**: Some areas, particularly conflict zones, may be inaccessible, leading to under representation in survey findings.This is particularly the cause in North-Eastern Nigeria which as a result of criminal groups like Boko Haram, has made it virtually impossible to access that region safely.

A.2.4 Ethical Data Management and Reporting

Afrobarometer takes significant steps to ensure ethical data handling and dissemination:

- **Data Security**: Survey data are encrypted during storage and transmission, ensuring compliance with data protection regulations.
- **Transparent Reporting**: Reports explicitly document survey limitations, including regions excluded due to security or logistical challenges.
- **Avoiding Harm**: Results are contextualized to prevent misinterpretation or harm to surveyed populations. Findings are shared responsibly, avoiding language that could inflame tensions.

A.2.5 Limitations and Future Ethical Enhancements

Despite its robust framework, Afrobarometer's approach could be improved in the following areas:

- **Inclusion of Marginalized Populations**: Future surveys could include anonymous digital surveys to take from institutionalized or transient populations.
- **Addressing Non-Response Bias**: Enhanced recruitment strategies, such as partnerships with community organizations, could increase participation among underrepresented groups.
- **Community Engagement**: Sharing results directly with communities through accessible formats (e.g., infographics or local town halls) would increase transparency and accountability.

A.2.6 Conclusion

The ethical considerations underpinning Afrobarometer's methodology ensure the credibility and validity of its findings while safeguarding respondent dignity. However, addressing remaining gaps—such as the exclusion of certain populations and challenges in conflict zones—would further enhance the ethical rigor of corruption perception research in Africa. By adhering to established ethical frameworks and remaining responsive to emerging challenges, studies like this can continue to give important information while maintaining the highest ethical standards.To do my part in ensuring ethical standards are upheld, i have included a datasheet for the Afrobarometer dataset.

B Amina's Story - A Personal Perspective

Amina is a 25-year-old woman living in Lagos, Nigeria. She works long hours at Balogun Market, navigating the daily challenges of urban life. She recently completed university, an achievement she's proud of, and dreams of one day pursuing higher education. But like many young Nigerians, Amina often feels frustrated and disillusioned when it comes to governance and corruption.

In conversations with her friends and colleagues, Amina's voice often reflects anger and disappointment. She believes corruption in the presidency is widespread, a sentiment shared by many in her age group and educational background, as revealed in the survey data. Growing up in Lagos, where access to news and social media is plentiful, Amina has been exposed to stories of corruption and unfulfilled promises. This exposure has shaped her outlook, making her skeptical of government accountability.

Amina's experiences highlight the role of demographic factors in shaping perceptions of corruption. Her youth connects her to a generation that is more vocal about demanding accountability, while her urban residency exposes her to more information about governance. At the same time, her level of education gives her the tools to critically analyze these issues, though it also fuels her frustration when systemic problems persist.

Reflecting on Amina's story reminds us of the ethical responsibility to consider the individuals behind the data. Every statistic represents a life, a struggle, and a hope for change. By thinking of people like Amina, policymakers and campaigners can design anti-corruption initiatives that genuinely resonate with those they aim to serve. Ethical actions begin with understanding these lived realities, ensuring that interventions are meaningful and respectful of the diverse experiences within the population.

C Additional data details

This figure provides an overview of demographic variables and corruption perceptions from the Afrobarometer Nigeria Round 9 survey. Rural residents constitute a larger share of the sample, aligning with Nigeria's predominantly rural demographic landscape. Corruption perception data shows that "High Corruption" and "Some Corruption" dominate public opinion. The education level distribution highlights the prevalence of basic education, with the majority of respondents having completed secondary school. Finally, the age distribution indicates that the 25–34 age group is the most represented cohort.
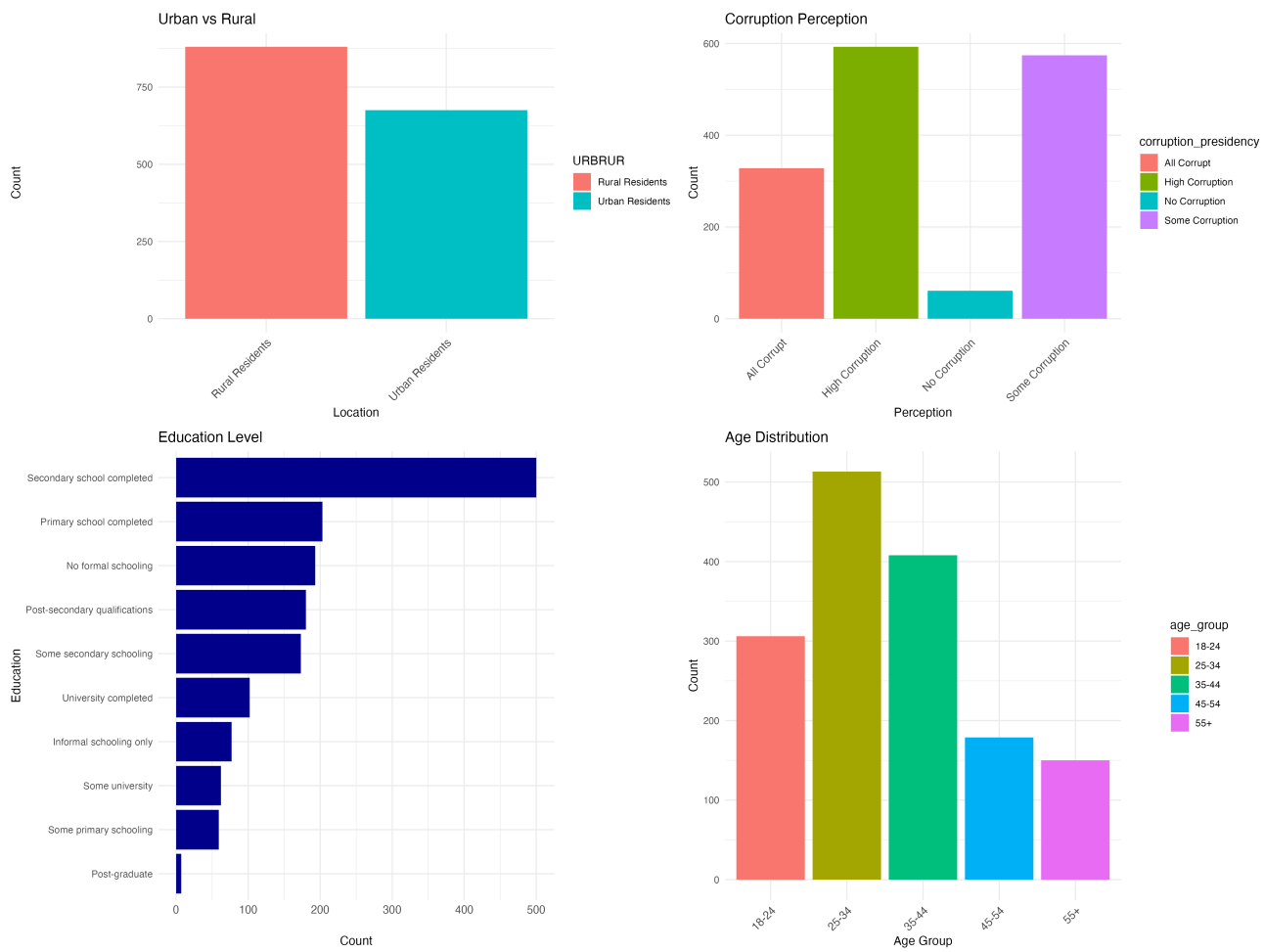
Figure 6: Demographic Distributions of the Afrobarometer Data
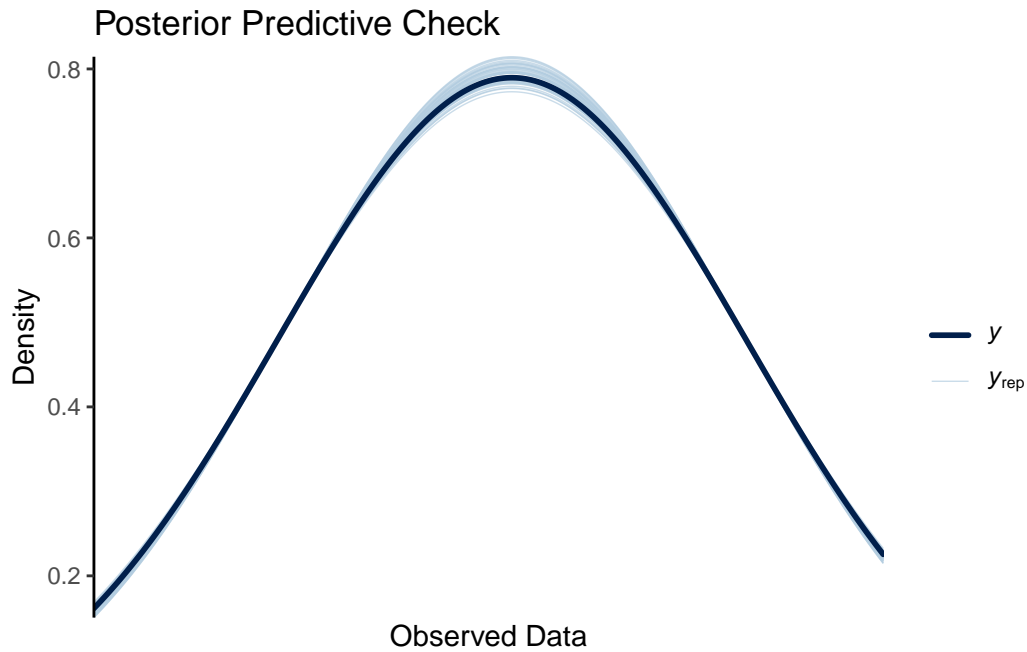
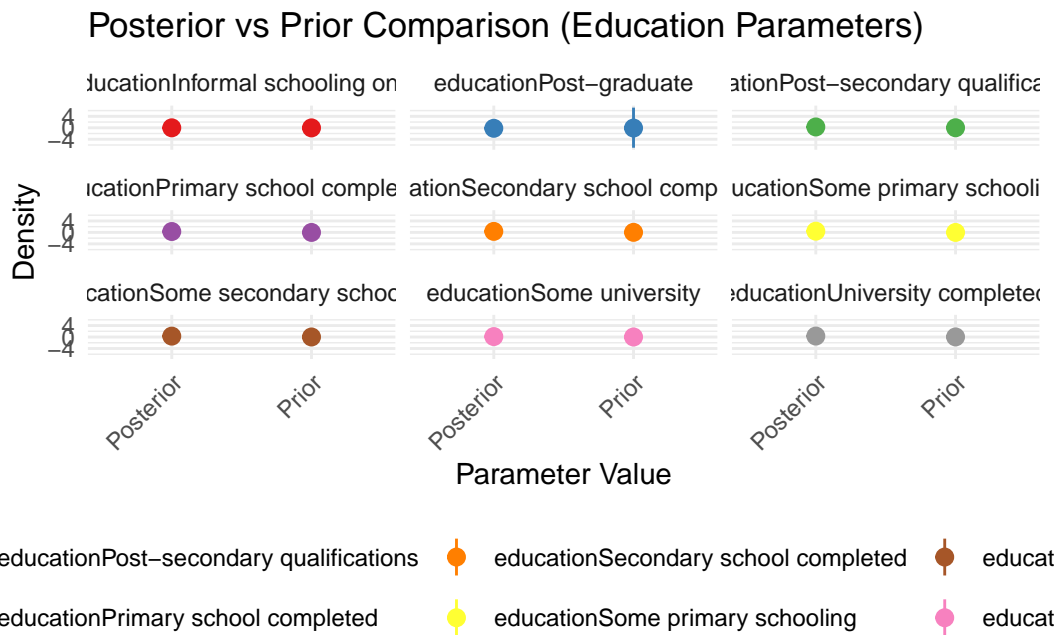Figure 7: Posterior Predictive Check for the Bayesian ordinal logistic regression model.

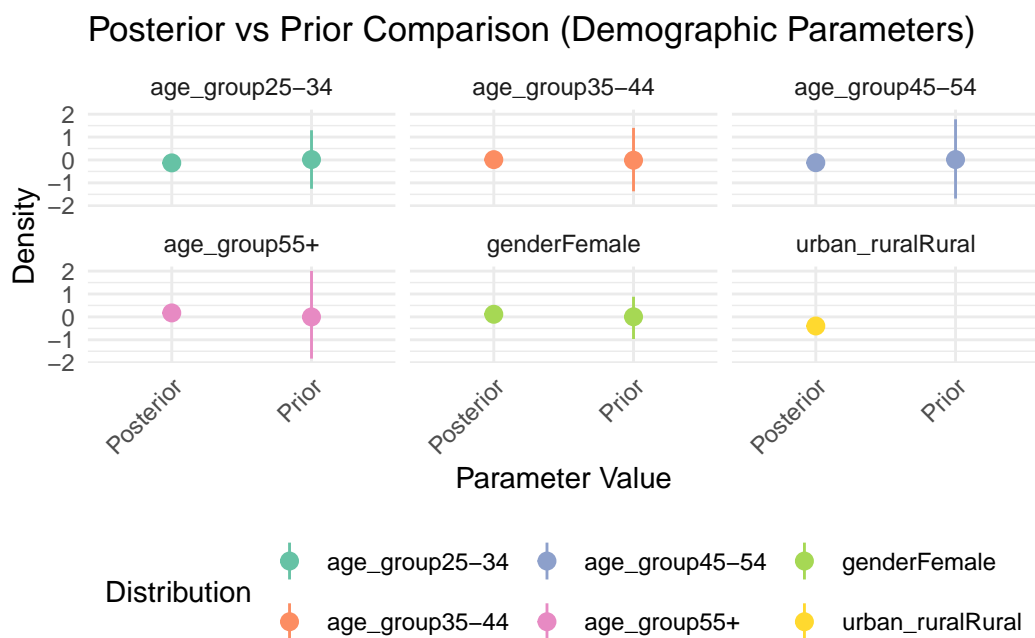Figure 8: Posterior vs Prior Comparison for Education Parameters.

Figure 9: Posterior vs Prior Comparison for Demographic Parameters.

D Model details

D.1 Posterior Predictive Check

D.2 Diagnostics
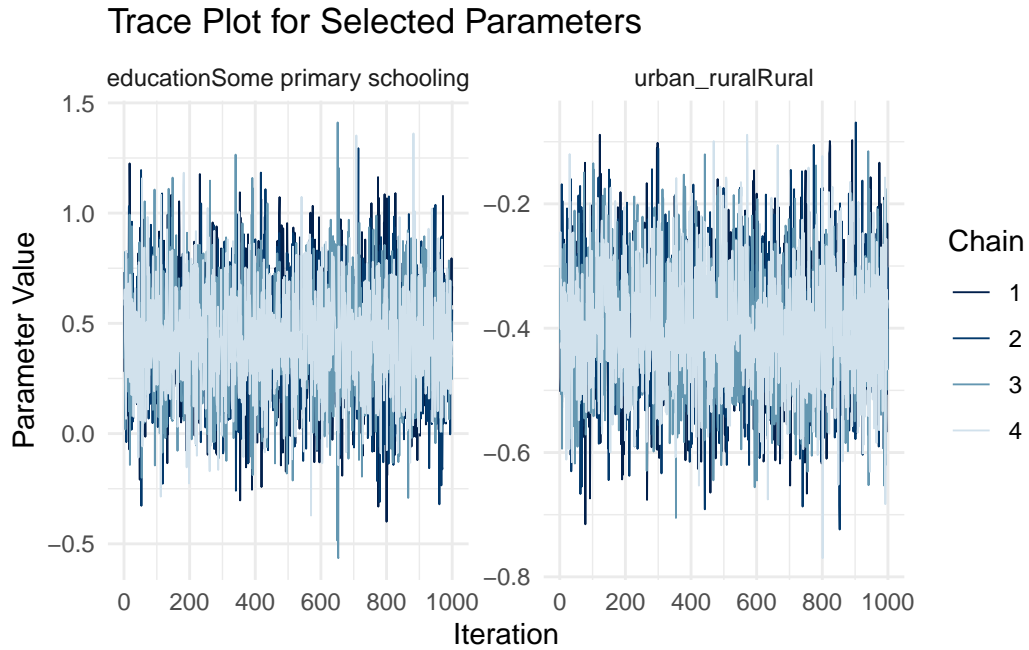
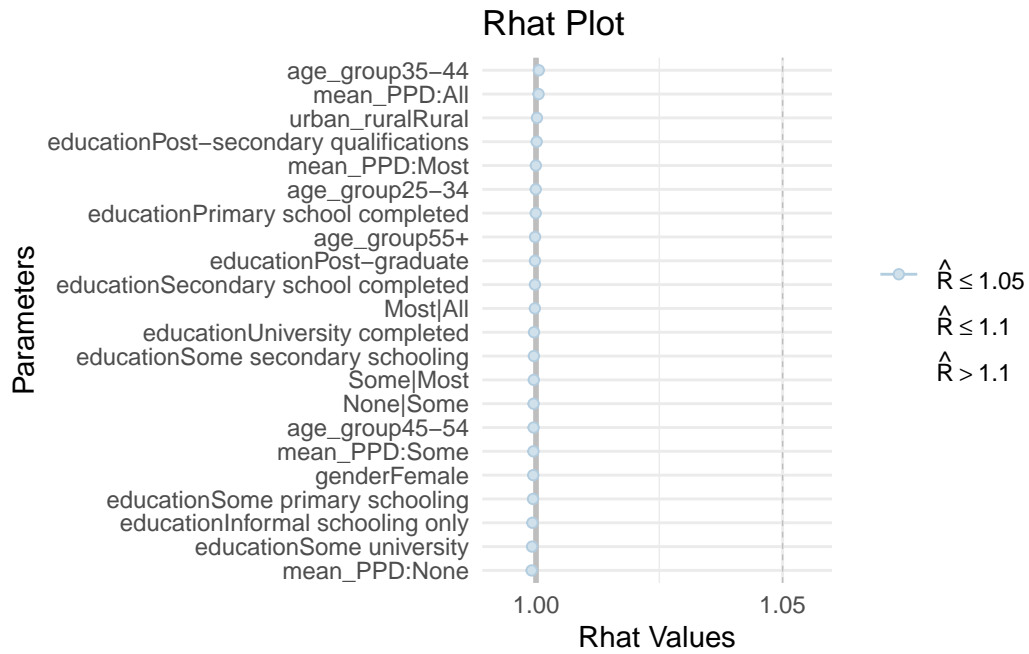Figure 10: Trace plot for selected parameters in the Bayesian ordinal logistic regression model.

Figure 11: Rhat values for model convergence in the Bayesian ordinal logistic regression model.
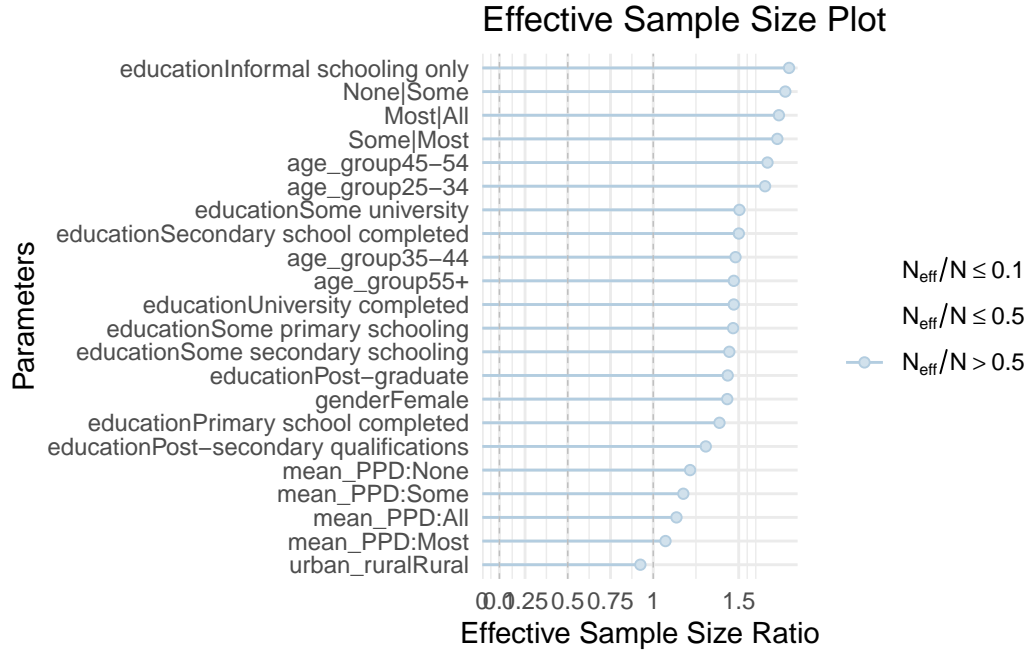
Figure 12: Effective sample size plot for parameters in the Bayesian ordinal logistic regression model.

References

Afrobarometer. 2022a. *Afrobarometer Nigeria Round 9 Codebook, 2022.* https://www.afrobarometer.org/survey-resource/nigeria-round-9-codebook-2022/.

———. 2022b. *Afrobarometer Round 9: Survey Manual.* https://www.afrobarometer.org/wp-content/uploads/2022/07/AB_R9.-Survey-Manual_eng_FINAL_20jul22.pdf.

———. 2023. "Afrobarometer Round 9, Nigeria, 2023." Afrobarometer Network. https://www.afrobarometer.org/survey-resource/nigeria-round-9-data-2023/.

Alexander, Rohan. 2023. *Telling Stories with Data.* Chapman; Hall/CRC. https://tellingstorieswithdata.com/.

Arel-Bundock, Vincent. 2022. "modelsummary: Data and Model Summaries in R." *Journal of Statistical Software* 103 (1): 1–23. https://doi.org/10.18637/jss.v103.i01.

Armah-Attoh, Daniel, E. Gyimah-Boadi, and Annie Barbara Chikwanha. 2007. "Corruption and Institutional Trust in Africa: Implications for Democratic Development." Afrobarometer Working Paper No. 81. Afrobarometer. https://www.afrobarometer.org/publications.

Bolker, Ben, and David Robinson. 2024. *Broom.mixed: Tidying Methods for Mixed Models.* https://CRAN.R-project.org/package=broom.mixed.

Gelman, Gabriel, Jonah Gabry, et al. 2021. *Bayesplot: Plotting for Bayesian Models.* https://mc-stan.org/bayesplot.

Müller, Kirill. 2020. *Here: A Simpler Way to Find Your Files.* https://CRAN.R-project.org/package=here.

Organization for Security and Co-operation in Europe. 2021. "Gender and Corruption: What Do We Know?" https://www.osce.org/files/f/documents/4/6/507569.pdf.

Pedersen, Thomas Lin. 2024. *Patchwork: The Composer of Plots.* https://CRAN.R-project.org/package=patchwork.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing.* Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Richardson, Neal, Ian Cook, Nic Crane, Dewey Dunnington, Romain François, Jonathan Keane, Dragoș Moldovan-Grünfeld, Jeroen Ooms, Jacob Wujciak-Jens, and Apache Arrow. 2024. *Arrow: Integration to 'Apache' 'Arrow'.* https://CRAN.R-project.org/package=arrow.

Rudis, Bob, Ben Bolker, and Jan Schulz. 2017. *Ggalt: Extra Coordinate Systems, 'Geoms', Statistical Transformations, Scales and Fonts for 'Ggplot2'.* https://CRAN.R-project.org/package=ggalt.

Team, Stan Development. 2021. *Rstanarm: Bayesian Applied Regression Modeling via Stan.* https://mc-stan.org/rstanarm.

Transparency International. 2019. "Global Corruption Barometer Africa 2019." Transparency International. https://www.transparency.org/en/publications/global-corruption-barometer-africa-2019.

Tricia Gower, Ernest N. Jouriles, Julie Pham. 2022. "Corruption and Its Psychological Implications: A Systematic Review." *Clinical Psychology Review* 94: 102159. https://doi.org/https://doi.org/10.1016/j.cpr.2022.102159.

U4 Anti-Corruption Helpdesk. 2023. "Corruption and Anti-Corruption Efforts in Nigeria." Transparency International/U4 Anti-Corruption Resource Centre. https://www.u4.no/publications.

United Nations Office on Drugs and Crime (UNODC). 2024. "3rd Corruption Survey in Nigeria: Executive Summary." https://www.unodc.org/conig/uploads/documents/3rd_corruption_survey_exec_sum_2024_07_09_web.pdf.

United Nations Population Fund. 2023. "Country Programme Document for Nigeria (2023-2027)." https://nigeria.unfpa.org/sites/default/files/pub-pdf/dp.fpa_.cpd_.nga_.9_-_nigeria_cpd_-_eng.pdf.

Wickham, Hadley. 2016. *Ggplot2: Elegant Graphics for Data Analysis.* Springer-Verlag New York. https://ggplot2.tidyverse.org.

Wickham, Hadley, Romain François, Lionel Henry, Kirill Müller, and Davis Vaughan. 2023. *Dplyr: A Grammar of Data Manipulation.* https://CRAN.R-project.org/package=dplyr.

Wickham, Hadley, Evan Miller, and Danny Smith. 2023. *Haven: Import and Export 'SPSS', 'Stata' and 'SAS' Files.* https://CRAN.R-project.org/package=haven.

World Association for Public Opinion Research (WAPOR). 2018. "Code of Ethics." https://wapor.org/about-wapor/code-of-ethics/.

Xie, Yihui. 2021. *Knitr: A General-Purpose Package for Dynamic Report Generation in r.* https://yihui.org/knitr/.

Zhu, Hao. 2024. *kableExtra: Construct Complex Table with 'Kable' and Pipe Syntax.* https:

//CRAN.R-project.org/package=kableExtra.