Perceptions of Corruption in Nigeria*

Rural Nigerians and Less Educated Groups Report Higher Corruption

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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 yourger individuals are more likely to perceive high corruption, while rura 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 accountability in Nigeria

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

1 Introduction

Corruption is a very 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 thiis 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 gap 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 alot of disparities in corruption perceptions across demographic groups. Younger respondents and urban residents have higher perceptions of corruption, likely because of higer 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 leverage 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. A the UNODC emphasizes, 'targeted and effective anti-corruption policies will improve likes of Nigerian citizens" (Afrobarometer 2023).

The remainder of this paper is structured as follows; Section 2 detailed 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 explores the details of the Afrobarometer survey. Section C shows plots for Posterior predictive checks and Diagnostics as well as their analysis.

2 Data

2.1 Measurement

For this analysis, i use the Afrobarometer Round 9, Nigeria, 2023 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.

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 complex real-world dynamics, reducing them to quantifiable variables while maintaining their conceptual integrity.

This dataset captures a unique moment in Nigeria's socio-political landscape, reflecting 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 lack 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 valuable survey data for analysis.***Telling Stories with Data*** (Alexander 2023) was referenced for its code and 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
Some Corruption	Post-graduate	Female	35-44	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 2022). 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 key statistics to offer 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 insights 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 comprehensive snapshot of the dataset, enabling a clear understanding of its demographic and categorical variables.

2.3 Corruption Perceptions Vs Variables of Interest

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 reveals 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

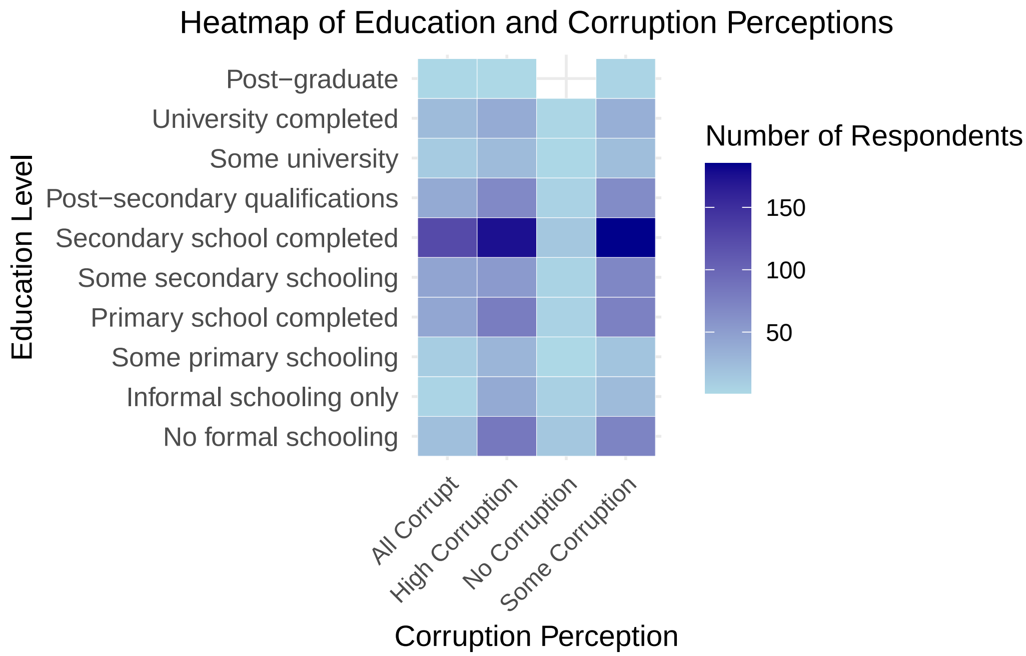

Figure 1: Relationship between Education Levels and corruption percetpions in Nigeria in Nigeria

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 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

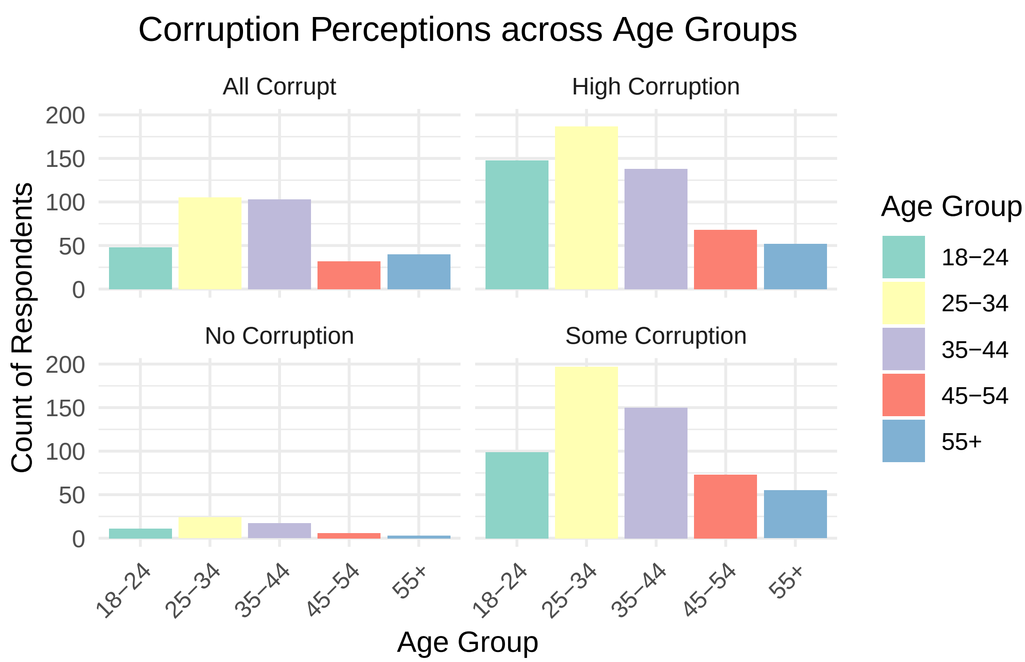

Figure 2: Age Group Vs. Corruption Perception. This faceted bar chart plots the relationship between the age group of respondents and their different corruption perception levels in Nigeria.

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.

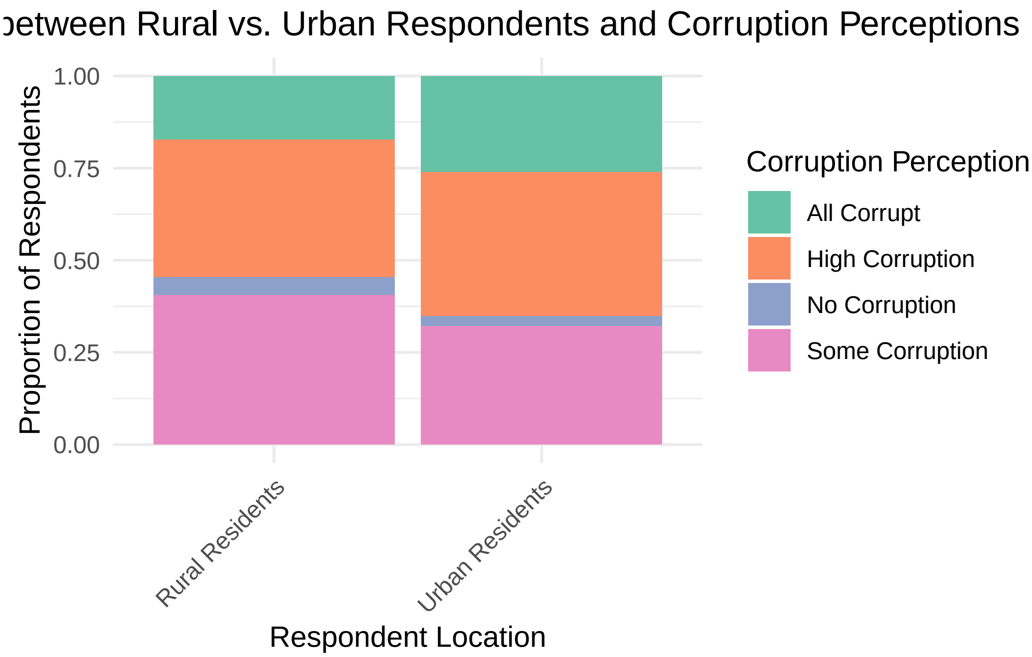

Figure 3: Rural/Urban Vs. Corruption Perception. This stacked bar chart visualises the relationship between respondents' corruption perceptions and weather they live in rural or urban areas in Nigeria.

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 reveals 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 shows the the relationship between respondents' gender (male and female) and their perceptions of corruption. Each panel represents one gender, displaying the count of respon-

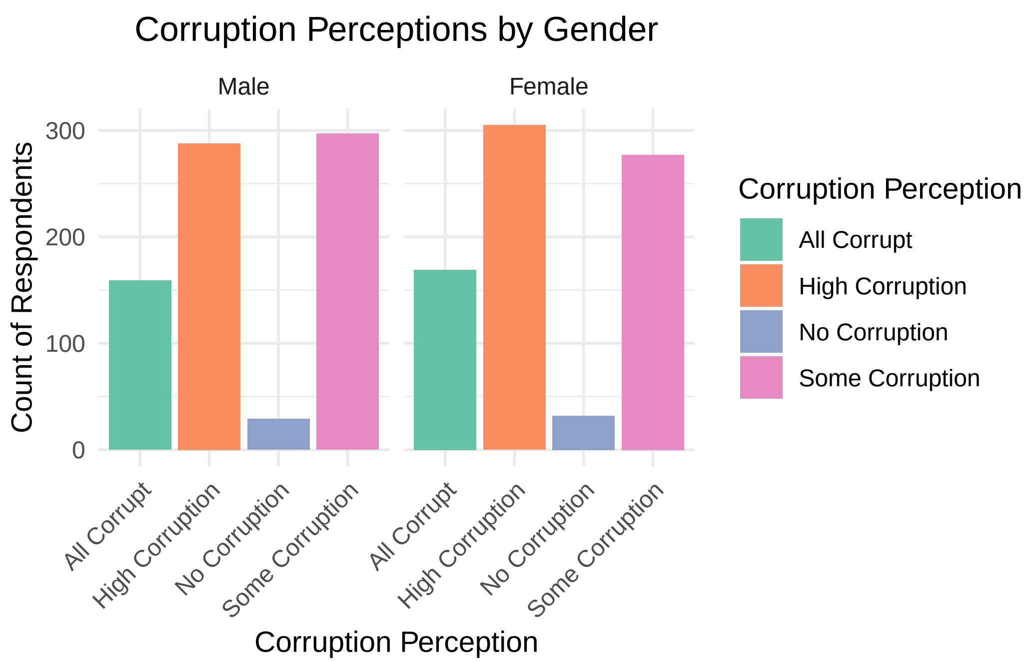

Figure 4: Gender Vs corruption perceptions. This faceted bar chart shows the relationship between a respondents' gender and how they perceive corruption within the presidency in Nigeria.

dents 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:

$$\log\left(\frac{P(y_i \leq j)}{P(y_i > j)}\right) = \alpha_j - (\beta_1 \times \text{education} + \beta_2 \times \text{gender} + \beta_3 \times \text{urban rural} + \beta_4 \times \text{age group}) \tag{1}$$

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

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: Summary of the Bayesian Model

term	estimate	std.error
educationInformal schooling only	-0.01	0.25
educationSome primary schooling	0.43	0.25
educationPrimary school completed	0.31	0.17
educationSome secondary schooling	0.32	0.19
educationSecondary school completed	0.35	0.17
educationPost-secondary qualifications	0.29	0.20
educationSome university	0.16	0.27
educationUniversity completed	0.34	0.23
educationPost-graduate	-0.18	0.74
genderFemale	0.11	0.10
urban_ruralRural	-0.40	0.10
age_group25-34	-0.13	0.13
age_group35-44	0.02	0.14
age_group45-54	-0.12	0.17

age_group55+	0.17	0.19
None|Some	-3.17	0.23
Some|Most	-0.32	0.21
Most|All	1.41	0.21

The analysis revealed distinct 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) arre associated with positive effects on corruption perceptions, indicating a greater likelihood of perceived higher levels of corruption. Begin 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. Agegroups show minimal variation in their association with corruption perceptions, with no significant deviations observed among different age brackets.

4.2 Predicted Probabilities

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 more advanced 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

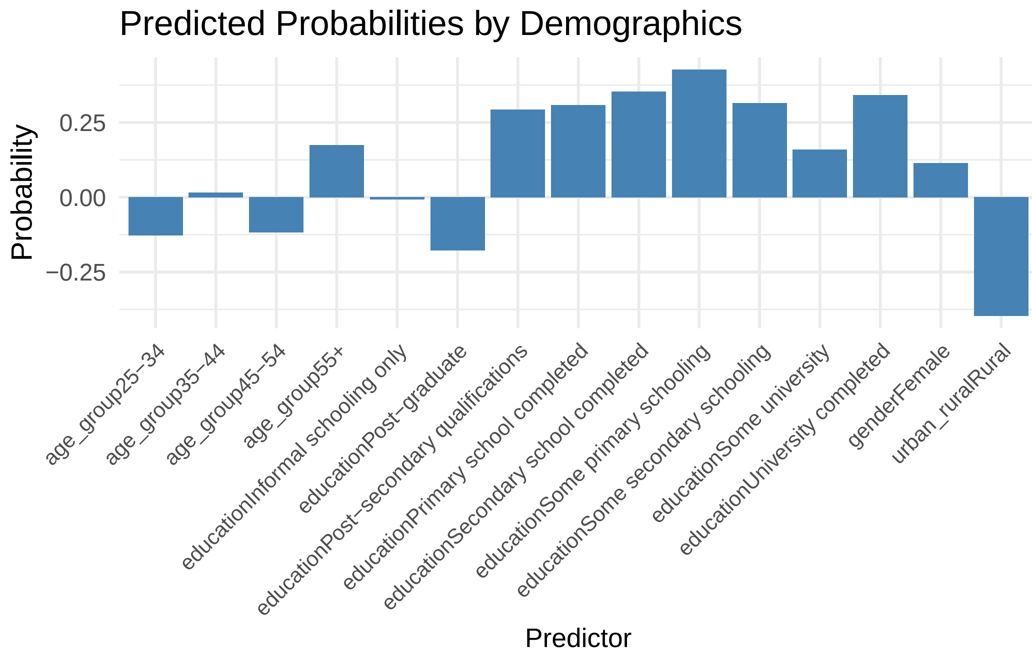

Figure 5: Predicted probabilities of high corruption perceptions by key predictors.

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 camapigns 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 beceause 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 critical 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 leveraged 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 a key 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 whistleblower protections are important steps to showing institutional accountability. Localized outreach through community leaders can also help bridge the trust gap, 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 Survey Methodolgy and Design

A.2 Sampling Techniques

A.3 Observational Data Challenges

A.4 Proposed Improvements

B Additional data details

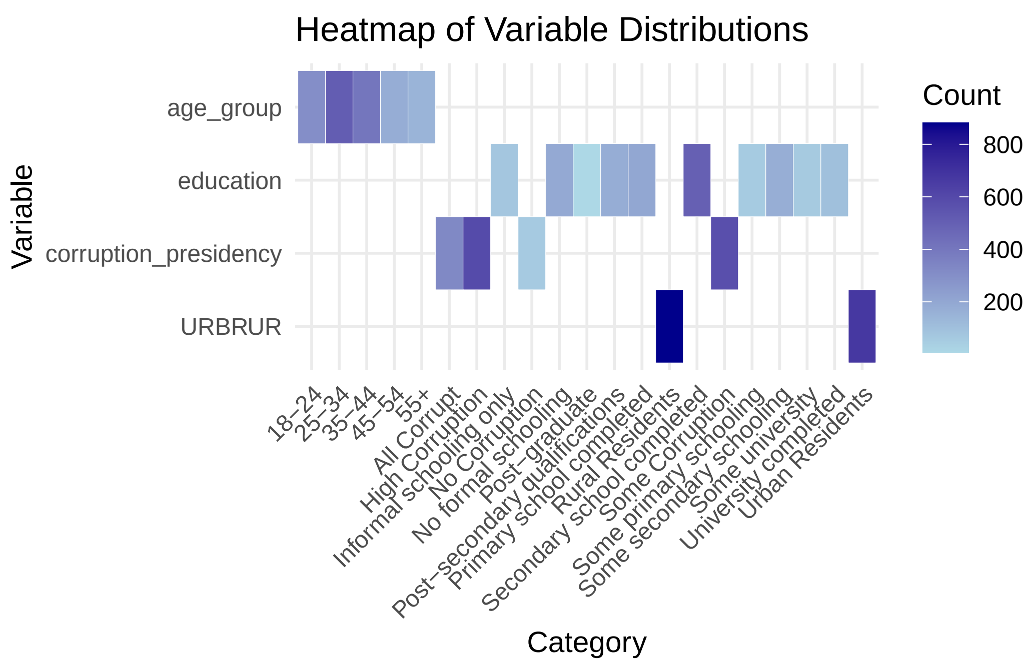

Figure 6: combined variables of interest

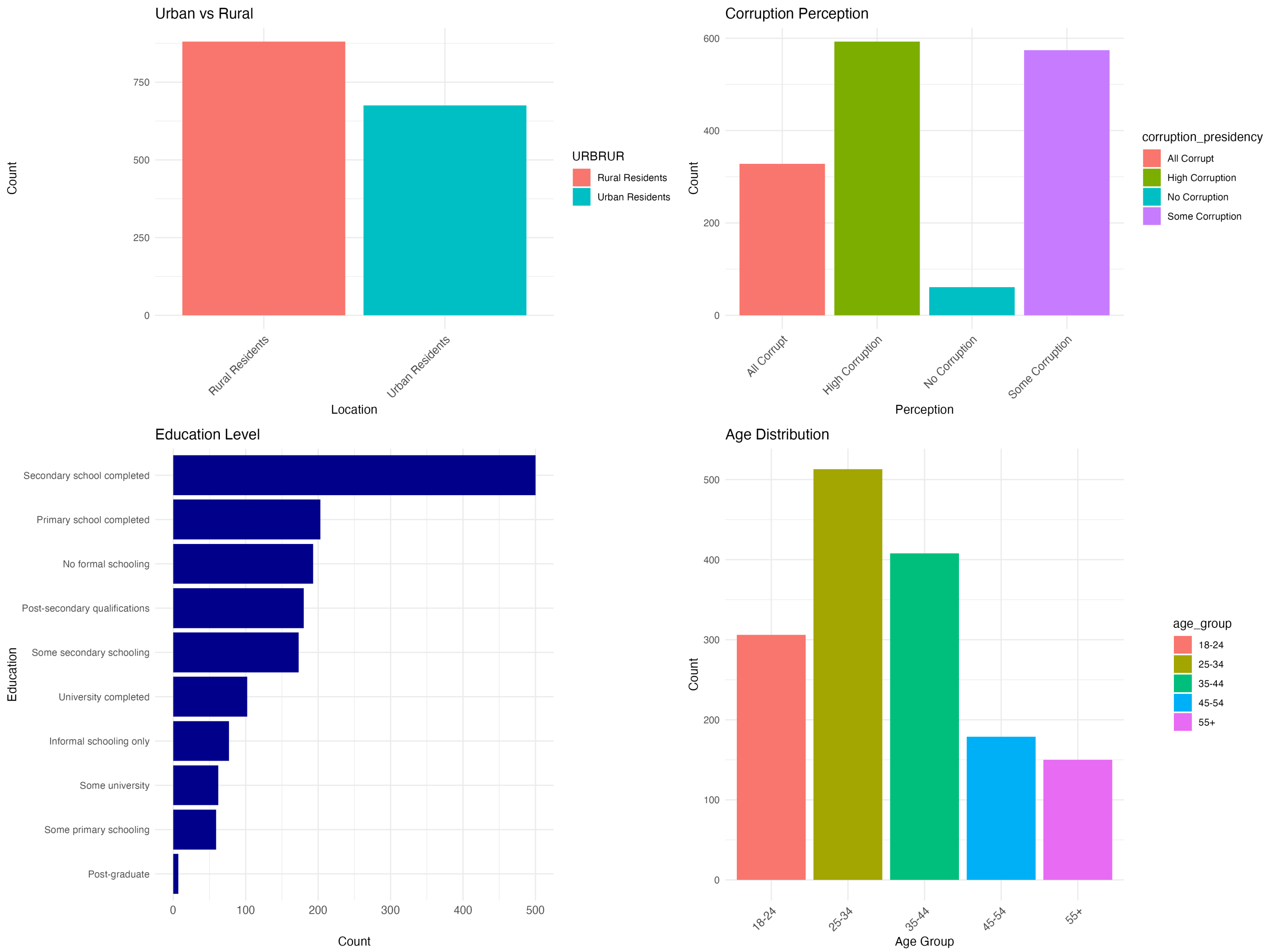

Figure 7: Combined plot

C Model details

C.1 Posterior Predictive Check

C.2 Diagnostics

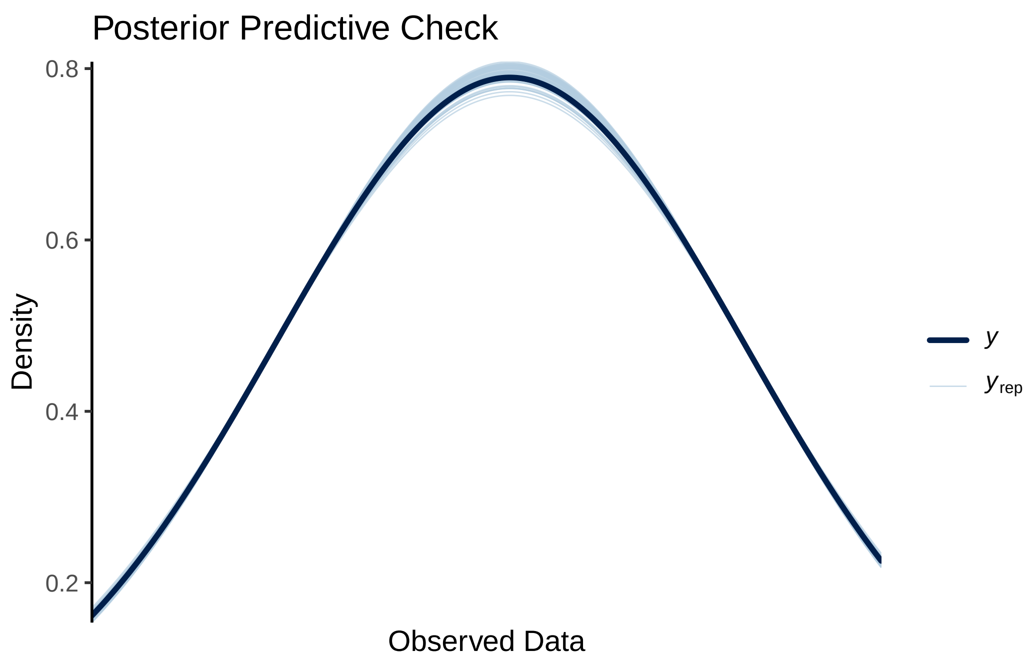

Figure 8: Posterior Predictive Check for the Bayesian ordinal logistic regression model.

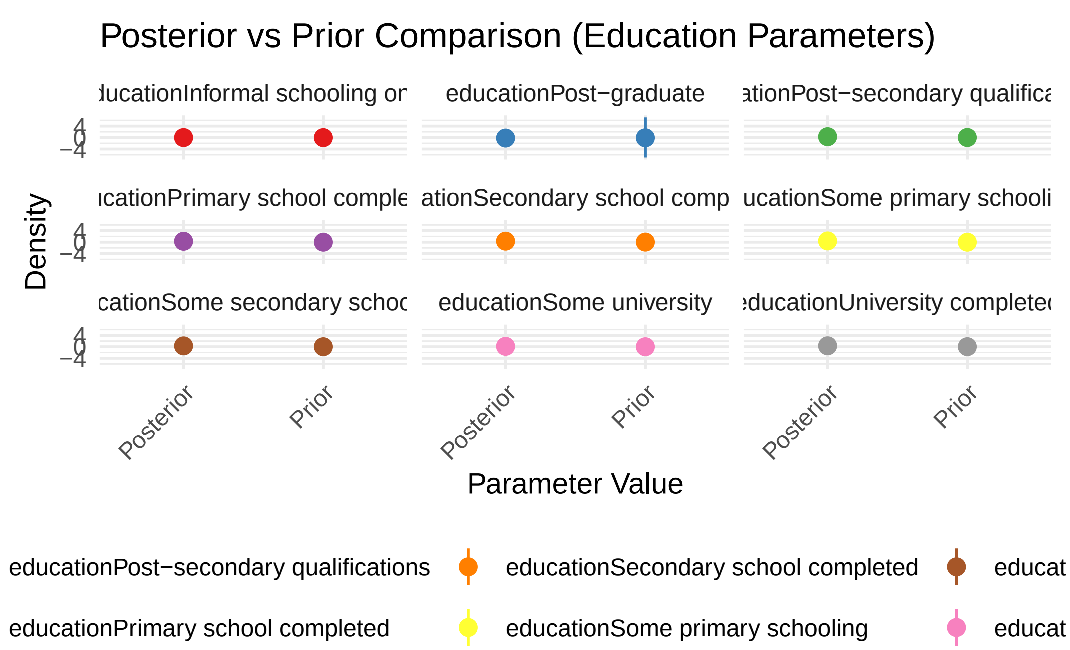

Figure 9: Posterior vs Prior Comparison for Education Parameters.

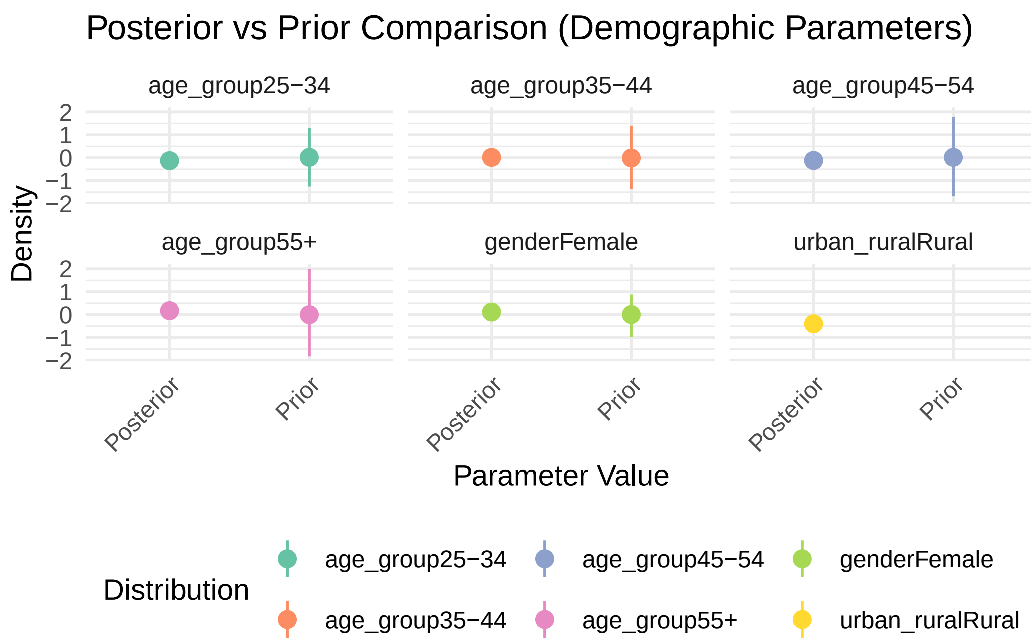

Figure 10: Posterior vs Prior Comparison for Demographic Parameters.

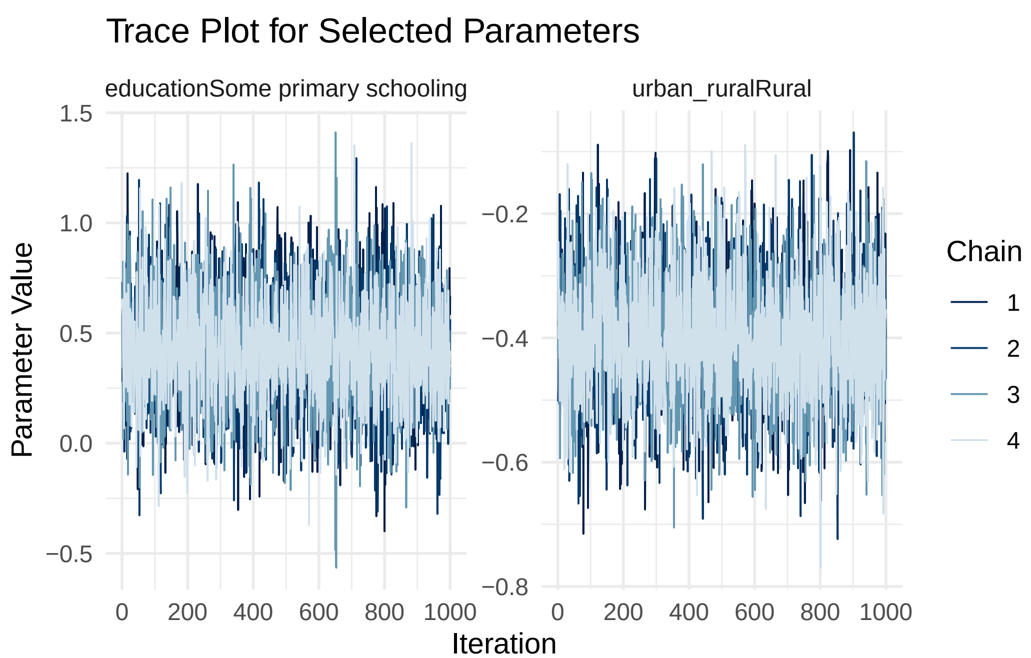

Figure 11: Trace plot for selected parameters in the Bayesian ordinal logistic regression model.

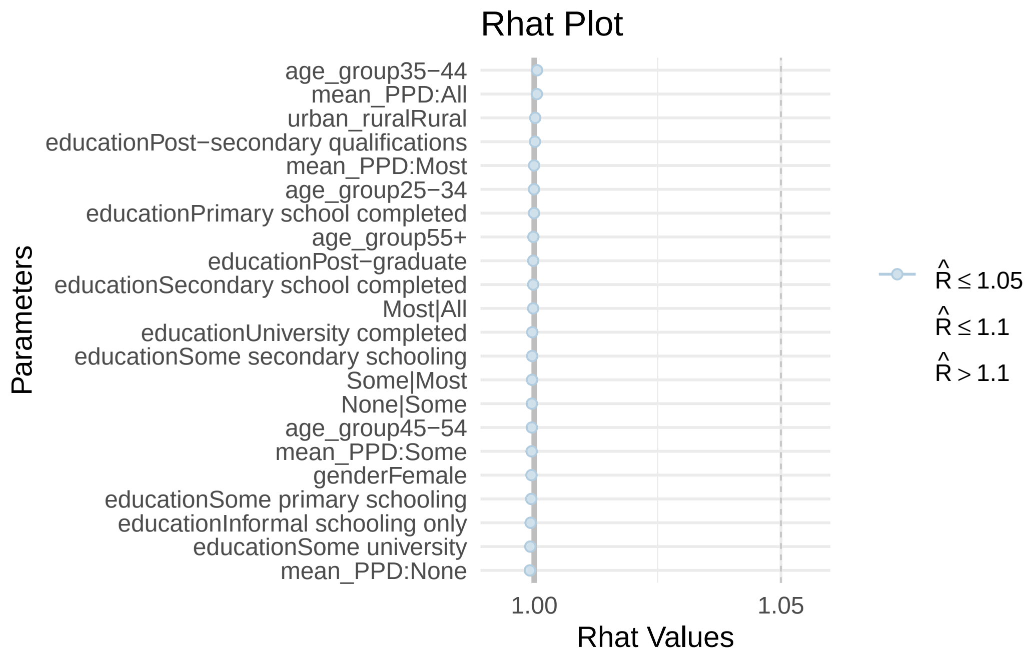

Figure 12: Rhat values for model convergence in the Bayesian ordinal logistic regression model.

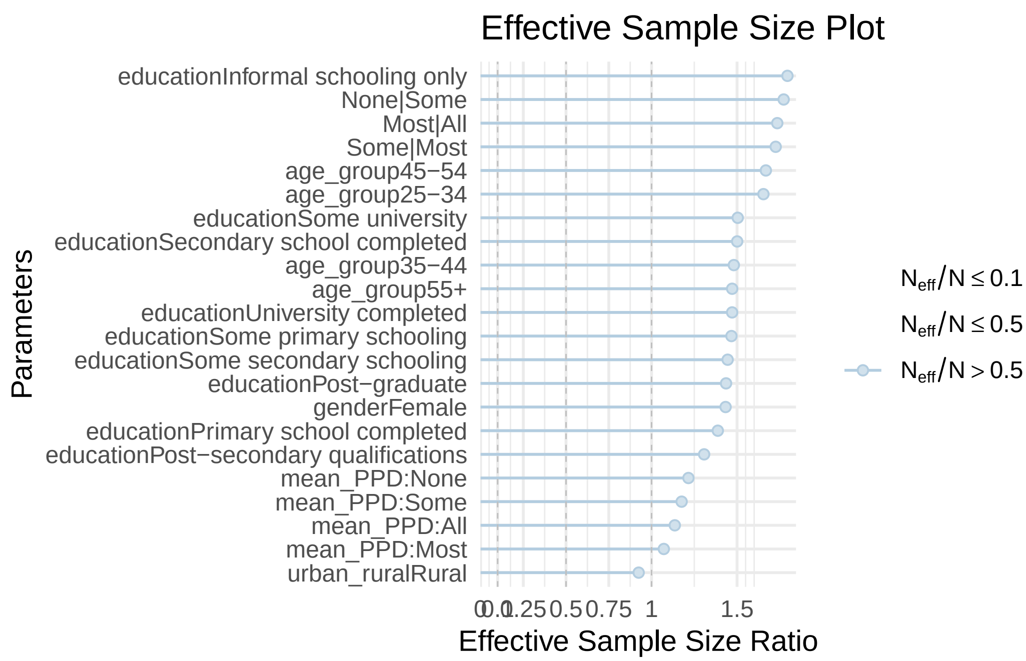

Figure 13: Effective sample size plot for parameters in the Bayesian ordinal logistic regression model.

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