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MULTIDIMENSIONAL POVERTY DETERMINANTS IN NIGERIA: AN ORDERED PROBIT ANALYSIS USING THE NATIONAL SOCIAL REGISTER

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ABSTRACT

Most studies on the determinants of poverty rely on traditional econometric approaches, such as linear regression or binary logit models, and have provided valuable insights but fail to provide the differences in how these determinants impact the diverse levels of poverty within the target population. This study bridges that gap by applying the Ordered Probit Model (OPM) to analyse multidimensional poverty determinants in india, utilizing data from the National Social Register (NSR) compiled by the National Social Safety-Net Office (NASSCO). The NSR, aggregating records from all 36 states and the Federal Capital Territory, provides a comprehensive socioeconomic database of over 15 million poor and vulnerable households nationwide. The study utilized the Proxy Means Test (PMT) scores categorized into deciles, which in turn are classified into three groups: extremely poor (1), poor (2), and moderately poor (3). The ordered probit results reveal that education, urban residence, and employment status are significant predictors of poverty reduction, with higher educational attainment and urban residency distinctly increasing the probability of escaping extreme poverty. In contrast, households in the North-East and North-Central zones, larger households, and those headed by females are significantly more likely to experience extreme poverty. Marginal effects analysis underscores the protective impact of tertiary education and waged employment while highlighting the persistent disadvantages faced by female-headed and rural households. These findings expose pronounced regional, gender, and urban-rural disparities in poverty dynamics, emphasizing the need for geographically targeted interventions, expanded educational opportunities, particularly for women, and holistic rural development strategies. The study contributes robust empirical evidence for policymakers aiming to disrupt rooted poverty cycles and promote inclusive socioeconomic developments.

Keywords: Multidimensional poverty, Ordered probit Model, Marginal Effects, National Social Register, Nigeria,Proxy Means Test, Poverty determinants.

1.0 Introduction

Poverty has remained a threat and challenge to humanity in all ramifications. It is complex, multidimensional and multifaceted with manifestations in the economic, social, political, environmental and every realm of human existence (Danaan, 2018). It is no wonder that Poverty reduction has been central in development debates in the past two decades, with the success of development policies being measured according to how well they tackle poverty (Jaiyeola & Bayat, 2020). Poverty is most peculiar in developing countries of Latin America, Asia, Africa and Nigeria specifically (Oshewolo, 2010).

The incidence of poverty in Nigeria has increased since 1980. The Federal Office of Statistics now National Bureau of Statistic (1999) reported that while poverty incidence was 28.1% in 1980, it rose to 46.3% in 1985 and decreased to 42.7% in 1992 and later rose to 65.6% in 1996. In 2004 it decreased to 54.7 % and in 2010 the figure shot to 60.9% (NBS,2012). A decade later in 2020 the apex statistical Office reported that 40% or 83 million Nigerians live in poverty. Although Nigeria's poverty profile for 2021 has not yet been released, it is estimated that the number of poor people will increase to 90 million, or 45% of the population, in 2022 (NBS,2020) If the World Bank's income poverty threshold of $3.20 per day is used, Nigeria's poverty rate is 71% compared to lower rates for some oil-producing developing countries like Brazil (9.1%), Mexico (6.5%), Ecuador (9.7%) and Iran (3.1%), this is grim.(World Bank,2022).

The historical context of poverty analysis shows a significant shift in focus over time. In the 1960s, poverty assessments mainly relied on income-based indicators. However, by the 1990s and beyond, researchers and policymakers increasingly turned their attention to non-monetary measures. The traditional income-centric approach has faced criticism for its narrow scope, as it fails to account for the multidimensional nature of poverty including deprivations in education, healthcare, and other essential services (World Bank, 1990)

Poverty is a multidimensional phenomenon. In Nigeria its a complex and deeply entrenched issue, cutting across multiple dimensions of well-being ranging from income and education to health and living standards. Despite numerous policy efforts, millions of Nigerians remain trapped in varying degrees of deprivation, with some hovering just above the poverty line while others endure extreme destitution (NBS, 2022).Based on a 2022 multi-dimensional poverty survey report by the National Bureau of Statistics, 132.92 million Nigerians are categorized as multi-dimensionally poor.

Aderemi&Ogebe (2024) focused their research on widowhood poverty where they examine poverty transitions among widow-headed households, identifying key factors that influence their economic status. Using Markov transition probability models, they track how widow-headed households move between poverty states over time, revealing important patterns of mobility and persistence.The analysis demonstrates that while severely poor widows experience gradual improvements, non-poor widows tend to remain economically stable.The ordered logit models were also explored which identify how household characteristics affect the likelihood of falling into deeper poverty. These models clearly show that larger dependency ratios push widows toward severe poverty, while education and age serve as protective factors.The study's findings remain robust across alternative specifications and measurement approaches, lending credibility to both the results and the methodological framework. By integrating these complementary modelling techniques,Markov chains for dynamic analysis and logit models for static determinants, the study provide a comprehensive understanding of widow poverty that informs targeted policy interventions. The results strongly advocate for social protection measures including life insurance schemes and educational programs specifically designed to address the unique vulnerabilities faced by widows in African contexts.

In Nigeria, Apata et al (2010) conducted a study on the determinants of rural poverty with specific attention to the small holder farmers in the south- west zone. The study employed a Probit model on a sample of 500 smallholder farmers to establish factors that influences probability of households' escaping chronic poverty. Results show that access to micro-credit, education, participation in agricultural workshops/seminars, livestock asset, and access to extension services significantly influence the probability of households' existing chronic poverty. On the other hand, female headed households' and distance to the market increases the probability of persistence in chronic poverty. Thus, these variables are significant in capturing the key rural poverty determinants. However, gender disparities in property rights have a consequence on poverty, as women empowerment through legal rights to property as key chronic poverty ameliorating factors among the farming communities.

Traditional econometric approaches to studying poverty determinantssuch as linear regression or binary logit modelshave provided valuable insights but suffer from a critical limitation: they treat poverty as a uniform condition rather than a spectrum of severity. By focusing solely on whether households are poor or not, these methods overlook the crucial distinctions between those who are marginally poor, moderately deprived, or trapped in chronic, severe poverty. This oversight weakens the precision of policy recommendations, as interventions that might lift the "moderately poor" out of poverty could have little effect on those in deeper deprivation (Alkire & Foster, 2011).

This study seeks to bridge that gap by applying the Ordered Probit Model (OPM) to analyse multidimensional poverty determinants in Nigeria, using data from the National Social Register (NSR). The NSR, with its rich household-level data on deprivation indicators, is uniquely suited for this analysis, as it captures not just these indicators but also proxy means test scores used in classifying the poor and vulnerable household into deciles depicting varying intensities of deprivation. The Ordered Probit Model is particularly well-suited for this research because it explicitly accounts for the ordinal nature of poverty severity. Unlike standard regression models that assume poverty is either present or absent (a binary outcome) or that differences between poverty levels are uniformly spaced (as in linear models), the OPM recognizes that poverty exists in ordered categoriessuch as non-poor, moderately poor, and severely poorwithout imposing arbitrary numeric distances between them.

The choice of the Ordered Probit Model is further justified by its ability to reveal how different factorssuch as education, employment, or access to healthcareexercise varying degrees of influence depending on where a household falls along the poverty spectrum. For example, while improved education might help move moderately poor households out of poverty, its effect on the severely poor could be muted due to intersecting barriers like lack of infrastructure or social exclusion. Conventional models overlook these key differences, but the OPM can detect them, making it a more powerful tool for policymakers who need to design targeted interventions for different poverty segments.

Moreover, the OPM's robustness in handling latent variable constructs aligns well with multidimensional poverty measurement, where deprivation is often inferred from a range of observed indicators rather than a single metric. Since the NSR includes data on multiple welfare dimensionssuch as Education, Employment, Place of Residence, Geographic Zone and Household Features, the OPM's capacity to model an underlying, unobserved "poverty propensity" that manifests in ordered categories makes it a natural fit for this analysis.

Given Nigeria's pressing need for evidence-based poverty reduction strategies, this study's use of the Ordered Probit Model offers a methodological advancement over prior research. By moving beyond simplistic poverty classifications, it provides a more detailed understanding of how determinants operate across poverty intensities which is a crucial step toward crafting policies that are not just broad but precisely calibrated to lift all segments of the poor out of deprivation.

1.1 Statement of the Problem

Econometric studies on the determinants of poverty mostly rely on the traditional regression approach, which mainly gives attention to the mean or expected value of the response variables. While appreciating the helpful estimations this technique provides, it fails to provide the differences in how these determinants impacts the diverse levels of poverty within the target population. Explicitly, the method is unable to portray the disparities that is inherent among the different category of the poor, each having peculiar deprivation status.

This gap is also similar to poverty related studies carried out in Nigeria, where attention is mostly given to identifying determinants and their overall impact on poverty neglecting the substantial disparity in poverty intensity among the different subcategories. Consequently, necessary insights into how specific determinants influence different levels of poverty remain unexamined.To proffer solution to this problem, the Ordered Probit Model is employed which takes into cognisance the ordinal nature of poverty severity.This technique gives a more robust insight on the determinants of poverty that may have remained hidden in conventional regression techniques.

2. Sources of Data

This research used the National Social Registry (NSR) of the Poor and Vulnerable Households (PVHHs) in Nigeria which is obtained from the National Social Safety-Net Office (NASSCO). The NSR is the sum aggregate of all the State Social Registers (SSRs) of the 36 states of the Federation including the FCT. The building of the NSR spans between 2016 to date, however, the study will be based on data turned in from inception to March 2024 and will focus on six states which are Ebonyi (South- East), Cross Rivers (South South), Ekiti (South -West), Sokoto (North- West) Taraba (North -East) and Niger (North-Central). The states are purposefully selected based on the National Living Standard Survey (NLSS 2018/2019) conducted by the National Bureau of Statistics which reported the six selected state as having the highest poverty headcount in their respective zones (see table 2.1)

Table 2.1: Poverty Headcount rate of Selected States

State	Zone	Poverty Headcount rate (%)
Taraba	North-Central	87.72
Cross River	South-South	36.29
Ebonyi	South- East	79.76
Sokoto	North- West	87.73
Niger	North-central	66.11
Ekiti	South-West	28.04

Source: National Bureau of Statistics

3.0 Techniques for Data Analysis

Theoretical Model: The broad model encompasses five dimension that hypothesize Poverty level as a function of Education, Place of Residence, Geographical Zone, Employment and Household Features

$$POV_{PMT} = F\ (ED_d, PR_d, GZ_d, EM_d , HF_d) \ldots\ldots 3.1$$

Where:

POV_{PMT} = *Poverty level represented by the PMT Scores*

ED_d = *Education dimension*

PR_d = *Place of Residence dimension*

EM_d= *Employment dimension*

HF_d= *Household Features Dimension*

Table 3.1: Poverty Dimensions Description.

		Predictor Variables
Dimensions	**Categories/Variables**	**Description**
Education	No Education =1	The Head of Household has no form of Education
	Primary Education =2	Household head that has completed only primary school education

	Secondary Education =3	Household head that has completed Secondary school education
	Tertiary Education=4	Household head that has completed Tertiary school education
Place of Residence	Rural =1	Household is located in rural area
	Urban=2	Household is located in urban area
Geographical Zone	North-West =1	Household reside in the North- West zone of the country
	South_West=2	Household reside in the North- Central zone of the country
	North_Central=3	Household reside in the North – East zone of the country
	North_East=4	Household reside in the South- East zone of the country
	South_East=5	Household reside in the South-South zone of the country
	South_South=6	The Household reside in the South-West zone of the country
Employment Status	Unemployed =1	Household Head is not employed
	Pensioner =2	Household Head is Self employed
	Waged_Employment=3	Household Head is in waged employment
	Self_Employed= 4	Household Head is an Unpaid Family Worker
	Unpaid_family_Worker=5	Household Head is a Pensioner
Household Features	Age	Age of the Household Head
	Sex (male=1 female=2)	Sex of Household Head
	Household Size	Number of the Household Members
		Response Variable
Response Variable	**Model**	**Poverty level**
(PMT Scores)	Ordinal Probit Model	1= extremely poor, 2 = moderately poor, 3 = poor

Source: Modified From Bikorimana and Sun (2020)

Table 3.2: PMT Scores Range for Decile Categorisation

PMT Scores Range	Decile
11.354728 < 1	1
11.354728 - 11.537236	2
11.537236- 11.690346	3
11.690346- 11.823936	4
11.823936- 11.962916	5
11.962916- 12.104585	6
12.104585- 12.266036	7
12.266036- 12.444875	8
12.444875- 12.666751	9
12.666751- above	10

Source: National Social Safety – Net Coordinating Office (NASSCO)

The above table shows the categorization of the poor and vulnerable households into deciles based on the range of the PMT scores. The scores are calculated using the observable **and verifiable household characteristics** that serve as a proxy for household welfare. The lower the decile the higher the severity of poverty in the household.

Table 3.3: Response Variable for the Ordered Probit Model

Poverty Level	Value	Decile
Extremely Poor	1	1-3
Poor	2	4-6
Moderately poor	3	7-10

Source: Author

The decile is used to classify the poor households into three groups: extremely poor=1, poor =2, and moderately poor= 3. The households that are the in range of 1 to 3 deciles are extremely poor and those between 4 and 6 are categorized as poor while moderately poor are HHs between

3.1 Ordinal Probit Model

The probit model is an alternative to the logit model. This model belongs to the family of generalized linear models. It is used when the dependent variable is two-category and multi category, as in the logit model. It is seen that the ordinal probit model is widely used if the values of the dependent variable take more than two values and are in an ordered structure. In this model, as in the logit model, parallelism assumption is required. Both models give very similar results. However, the logit model is more popular than the probit model. One of the most important reasons for this is that while the logit model uses OR (Odds Ratio) values, wich are easier to interpret while calculating the coefficients, the cumulative normal distribution is used in the probit model (Güneri et al,2022)

The Ordinal Probit (OP) model derives from the multinomial distribution, albeit with ranked categories, thus, its likelihood function is multinomially distributed. The multinomial distribution is an extension of the binomial distribution where, now, the number of parameters being modelled exceeds one(Richard and Atinuke,2016). The density function for the multinomial distribution is:

$$Pro(P|Y) = \prod_{i=1}^{n} \prod_{j=1}^{J} p_i^{\,y_{ij}} \qquad 3.2$$

To derive the cumulative ordinal probit (OP) generalized linear model (GLM) from the multinomial distribution, let the responses $j = 1, \ldots, J$ be arranged in order of magnitude, and α_j the corresponding thresholds associated with the ordering. Further let Y_i^* be a Gaussian random variable assumed to be latent and assigning values to α_j according to a regression function:

$$Y_i^* = X_i\beta + \varepsilon_i, \qquad 3.3$$

where X is $n \times p$ design matrix, β is a $p \times 1$ unknown vector of regression coefficients, and ε is the $n \times 1$ vector of independently and identically distributed $(i.i.d)$ measurement errors: $\varepsilon_i \sim N(0,1)$. Though the values of y_i^* cannot be directly observed, the rule that assigns y_i^* to α_j is that if y_i^* exceeds a given threshold, then, for example, a household falls in the j^{th} category of poverty. This culminates in cumulative multiple binary outcomes:

$$Y_i = \begin{cases} j, \alpha_{j-1} < y_i^* \le \alpha_j \\ 0, \text{otherwise}, \end{cases} \qquad 3.4$$

where $\alpha_j \in \mathbb{R}$, and $\alpha_1 < \alpha_2 \dots < \alpha_J$.

Clearly, Y_i^* in our application, refers to the Gaussian poverty level, and is asymptotic of the ordinal variable Y_i when $J \to \mp\infty$.

Our objective is to predict the probability of a household falling in or below the j^{th} category given the observed covariates $x = (x_1, \dots, x_n)^T$. This probability is determined by the values of the latent variable Y_i^*, and is given by

$$p(y_i = j|x_i) = p(\alpha_{j-1} < y_i^* \le \alpha_j) \qquad 3.5$$

Since Y_i^* is Gaussian, and ε_i is assumed to be normally distributed, the outcome is a probit model, implying that the probability of falling in or below the j^{th} category is:

$$\begin{aligned} p(y_i = j|x_i) &= p(\alpha_{j-1} - X_i^T\beta < \varepsilon_i \le \alpha_j - X_i^T\beta) \\ &= \Phi(\alpha_j - X_i^T\beta) - \Phi(\alpha_{j-1} - X_i^T\beta) \end{aligned} \qquad 3.6$$

where $\Phi(.)$ is the cumulative distribution function (cdf) for the standard normal $\varepsilon_i \sim N(0,1)$:

$$F(\varepsilon_i) = \left(\frac{1}{2\pi}\right)^{-\frac{n}{2}} \exp\left(-\frac{1}{2}\varepsilon_i^2\right). \qquad 3.7$$

Thus, the likelihood function for the parameters is

$$L(\beta,\alpha|y=j) = \prod_{i=1}^{n}\prod_{j=1}^{J}[\Phi(\alpha_j - X_i^T\beta) - \Phi(\alpha_j$$

Given the explanatory variables captured in table 3.1, the Ordered probit Regression model for the study is presented below.

Y_i^* = $\beta_0+\beta_1 PE$ $+\beta_2 SE$ $+\beta_3 TE$ $+\beta_4 UR+\beta_5 SW+\beta_6 NC+\beta_7 NE+\beta_8 SE+\beta_9 SS+\beta_{10} FE+\beta_{11} AF+\beta_{12} HS+\varepsilon_i$

3.9

y = 1 (Extremely Poor) if y* ≤ ζ1

y = 2 (Poor) if ζ1

y = 3 (Moderately Poor) if y* > ζ2

where:

Y* = the latent variable (not observed)

Y= the observed dependent variable (Extremely Poor, Poor, or Moderately Poor)

β_1– β_{12}= the coefficients of the explanatory variables

ε = the error term

ζ1 and ζ2 are the thresholds (unknown parameters to be estimated) and the explanatory variables are as captured in equation 3.9

3.1.1HypothesisFor MLE

Ho :Cov (β_i) = 0

H_1 :Cov (β_i) ≠ 0

Where *i*= 1…….12

The null hypothesis (Ho) stipulates that the coefficient of the covariates in the ordered probit model with y_j categories (j = 1…3) are equals to zero (i.e no significant effect on poverty). Conversely the alternative hypothesis (H_1) connotes that the coefficient of the covariates are not equals to zero implying significant effect on poverty

3.1.2 Marginal Effect

In ordinal probit regression, the marginal effect quantifies the change in the probability of transitioning from one category to another (e.g., from "somewhat likely" to "very likely") due to a one-unit increase in an independent variable, while holding all other variables constant. Because the dependent variable is ordinal, these marginal effects are unique to each category and can differ across categories. They are derived using the coefficients from the ordinal probit model, incorporating the cumulative normal distribution function (CDF) and the variance of the latent variable

3.1.3 Computation of Marginal Effects

The marginal effect of an increase in on the chance of selecting the h alternative is given by:

$$\frac{\partial(P_{ik})}{\partial(X_{ik})} = [F\ (\alpha_{j-1} - x_i^T\beta) - F\ (\alpha_j - x_i^T\beta)]\beta \qquad 3.10$$

The ordered probit model with j alternatives will have $j$sets of marginal effects. The marginal effects of each factor on the different alternatives sum to zero.

Table 3.4: Result of Ordered Probit Model

Poverty_Category							
Dimensions	**Covariates**	**Coef.**	**Std. Err.**	**Z**	**P>z**	**95%**	**Conf.**
	No Education(reference)						
	Primary_Education	0.30893***	0.01021	30.26	0.000	0.28892	0.32894
	Secondary_Education	0.60312***	0.01074	56.15	0.000	0.58207	0.62417
Education	Tertiary_Education	1.11986***	0.01595	70.22	0.000	1.08861	1.15112
	Unemployed(reference)						
	Pensioner	0.18541***	0.00838	22.13	0.000	0.16898	0.20183
	Waged_Employment	0.95734***	0.03649	26.24	0.000	0.88582	1.02885
	Self_Employed	0.30632***	0.01377	22.25	0.000	0.27934	0.3333
EmploymentStatus	Unpaid_family_Worker	0.54415***	0.05968	9.12	0.000	0.42717	0.66113
	Rural(reference)						
Place of Residence	Urban	0.72633***	0.00982	73.94	0.000	0.70708	0.74558
	North_West(reference)						
	South_West	2.43515***	0.01173	207.64	0.000	2.41217	2.45814
	North_Central	-0.36729***	0.01482	-24.78	0.000	-0.39634	-0.3382
	North_East	-0.44240***	0.01196	-36.98	0.000	-0.46584	-0.419
	South_East	1.85512***	0.01288	144.07	0.000	1.82988	1.88036
Geographicalzone	South_South	3.06806***	0.01554	197.41	0.000	3.0376	3.09852
	Household Size	-0.54785***	0.0027	-203.12	0.000	-.55313	-0.54256
Household	Male(refernce)						
Features	Female	-0.27322***	0.00749	-36.50	0.000	-	-0.2585

						0.28789	
	Age	0.00118***	0.00022	5.35	0.000	0.00075	0.00162
	/cut1	-0.46611	0.01568			- 0.49683	-0.4354
	/cut2	1.67450	0.01645			1.64227	1.70674

Source: Own estimates using Stata 15.1 software

Note: Significance level: *p ≤ 0.05, **p ≤ 0.01 and ***p ≤ 0.001.

Number of Observations: 194,261

The result of the ordered probit in Table 3.4 shows that all the variables are significant at the three levels(0.05, 0.01, and 0.001.) Just like the quantile model, only four variables (North-East, North-West, household size, and sex) have a negative relationship with the PMT scores. The remaining variables all have a positive relationship with PMT scores. Education has shown a high tendency for poverty reduction because all the categories of educational attainment increase the PMT scores as compared to no education. The higher the household's head level of education, the higher the capacity of the household to reduce poverty. Households residing in urban areas (0.72633) are more likely to reduce poverty as compared to those in rural areas. This submission is in line with the findings of the QR model

The estimation results also revealed that all the studied employment categories tend to increase the PMT scores of the households. However, households located in the North-East (-0.44240) and North-Central (-0.36729) negatively impacted the PMT scores indicating that household in these two zones are more probable to be in the extremely poor group as compared to households in the North-West. In likewise manner, the female-headed household (-0.27322) is most likely to be in the extremely poor group as compared to households headed by males. The positive relationship between age and PMT scores recorded in the QR model is also seen in the Ordered probit model

3.1.4 Predicted Probabilities

Figure 1 shows the predicted probabilities for the three poverty categories evaluated at the sample means of the data. The predictions in Figure 1 show that for any average poor and vulnerable household , the probability of being in extremely poor category (Pov Cat=1), poor (Pov Cat =2), or moderately poor category (Pov Cat =3) are respectively 0.0.655 0.251 and 0.094respectively

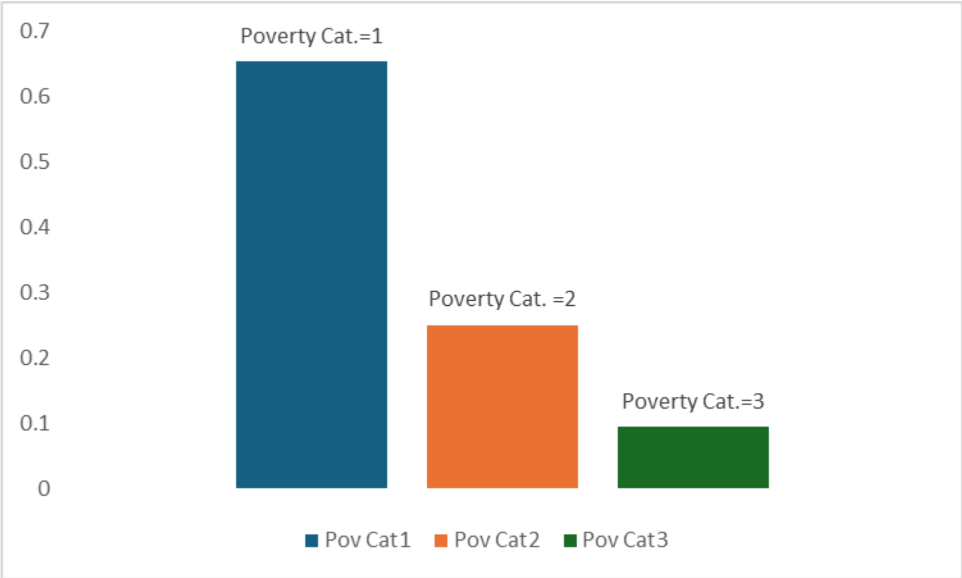

Figure 2: Predicted Probabilities for the three poverty categories

However, these probabilities are not very informative and sufficient, hence the need for marginal effects and the result is displayed in Table 3.5 below

Table 3.5The estimation results of the marginal effects of the explanatory variable based on the poverty category

Poverty Category				
Dimensions	**Variables**	**Extremely Poor =1**	**Poor=2**	**Moderately Poor =3**
Education	No Education *(reference)*			
	Primary Education	-.05476	.03157	.02319
	Secondary Education	-.11307	.06463	.04844
	Tertiary Education	-.22690	.12670	.10020
Place of Residence	Rural*(reference)*			
	Urban	-.14191	.08120	.06071
Geographical Zone	North-West*(reference)*			
	South_West	-.60693	.36066	.24627
	North_Central	.06470	-.06115	-.00355
	North_East	.07578	-.07178	-.00400
	South_East	-.48258	.35220	.13038
	South_South	-.69863	.28677	.41186
Employment	Unemployed*(reference)*			
	Pensioner	-.03149	.01731	01418
	Waged_Employment	-.18569	.10016	.08553
	Self_Employed	-.05326	.02920	.02406
	Unpaid_family_Worker	-.09887	.05395	.04492
Household Features	Age	-.00020	.00011	.00009

	Household Size	.09439	-.05213	-.04226
	Male *(reference)*			
	Female	.04692	-.02601	-.02092

Source: Own Estimates Using Stata 15.1

Marginal effects show the change in the predicted probability for each Poverty category for an average household given a unit increase in an explanatory variable. In the case of a categorical variable, the marginal effect is the change in the predicted probability given that a Household falls into a category of the variable. The estimation results from Table 3.5 shows that household head with Primary Education increase the probability of falling in the poor and moderately poor group by 3.2% and 2.3% respectively but unlikely to fall in the extremely poor group by 5.4%. Similarly, households whose head attained a tertiary education is more likely to be in the poor and moderately poor group by 12.7% and 10 % respectively and unlikely to be in the extremely poor group by 22.7 % as compared to household head without form of education

For households residing in the urban area, there is 8.1% and 6.1 % chance of being categorized under the poor and moderately poor group respectively. It is unlikely for these households to be in the extremely poor group by 14.2%. Households from North-East have a 7.6% tendency of being extremely poor and 6.5 % for North Central households as compared to the households in Northwest zone. The South-South household recorded the highest likelihood of being in the moderately poor category with 41.2 % when likened to households in the North-Western part of the country. This agrees with the result of the QR model where the south-south zone has the highest positive coefficient (0.58788) at the 75th quantile (moderately poor group). Households headed by Pensioners are more likely to be in the poor and moderately poor group by 1.7 % and 1.4 % respectively as compared to unemployed headed households. The household head in Waged employment are most unlikely to be extremely poor by 18.6 % and most likely to be in the poor group by 10%

The age of the household head is not significantly impactful on the PMT scores of the household as it is seen that the probability of households to be in the moderately poor is 0.009% while the size of the household is seen to meaningful impact on the likelihood of the household to be in the extremely poor group by 9.4%. Female headed households have a 4.6 % chance of being extremely poor as compared to the male-headed households

4.0 Conclusion

The ordered probit analysis provides an in-depth insight on poverty dynamics across Nigeria, revealing how geography, education, and household structure interweave to shape economic vulnerability. Our findings revealed a regional divide which shows households in the North-East and North-Central zones struggle with deeper poverty traps compared to other regions, while the South-South shows concentration in moderate poverty categories. Education emerges as the most potent equalizer, with its protective effects intensifying at higher levels of attainment. The recurrent disadvantage faced by female-headed households, in addition to the urban-rural divide, underscores the multidimensional nature of deprivation.

These findings call for well-tailored action by government and other stakeholders. Considering the significant negative effect of residing in the North-east and North-central zones on poverty reduction, decision makers should step-up targeted social interventionfor these regions with particular focus on households in the North-East zone given their high probability of being in the extremely poor group. In a related revelation, rural development initiatives should be prioritised to address the exclusive challenges encountered by rural poor and vulnerable households.

The discovery by the study that households whose head is engaged in waged employment is 18.6% less likely to be extremely poor points to the need to promote policies and program that will provide more opportunities for waged employment and intentionally enhancing the welfare of pensioners. The significant positive impact of education on poverty reduction calls for policy makers to increase access to education particularly for women and girls owning to the finding suggesting that female-headed households are more likely to experience poverty, highlighting the need for targeted support and empowerment programs for women.It suffices to add, while primary education shows modest benefits, the dramatic 22.7% reduction in extreme poverty probability from tertiary education argues for expanding university scholarships and technical education programs

The study's results also indicate that larger household sizes are associated with a higher likelihood of poverty, suggesting that family planning drive could be an effective strategy for poverty reduction. By implementing these recommendations, policymakers can develop targeted interventions to address the unique challenges faced by different populations and regions in Nigeria, ultimately reducing multidimensional poverty and promoting inclusive socioeconomic development

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