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Multilevel Analysis of Fertility Rate in Northern Nigeria

Mafolasire S.[1*], Mbah J. J.[2], Mikaeel F. H .[2], Ayorinde J. O.[3], Pam D. J.[1], Dayyab A. S.[1] and Nnaji A. H.[2]

[1]Department of Mathematical Sciences, Abubakar Tafawa Balewa University, Bauchi, Nigeria
[2]Department of Statistics, Federal College of Forestry, Jos, Nigeria
[3]Department of Pest Management Technology, Federal College of Forestry, Jos, Nigeria

Corresponding Author: sheyimafolasire@gmail.com

ABSTRACT

In this study the modification of the existing multilevel regression models was carried to analyze fertility rates in Northern Nigeria. By modifying the slope parameter, we aimed to improve the model's accuracy and compare its results to the original model. Additionally, we assessed the impact of fixed and random effects on the intercept. The data collected from Nigerian Demographic and Health Survey (NDHS), 2018, is used to validate the new model. Our analysis revealed that the modified model provided more accurate estimates of fertility rates compared to the unmodified model. Also, the impact of Fixed and Random effects on the regions (North-East, North-West, and North-Central), and the independent variables (Religion, Number of wives, Highest educational levels, Sex of child) was determined, it was discovered that the intercept and Education have significant effects with p-values of .000, indicating strong influence. Religion is marginally significant with a p-value of .051, while Sex of child has no significant effect (p = .798), the number of wives shows a highly significant effect (p = .001). The modified Multilevel Regression model is more robust than the unmodified Multilevel Regression model.

Keywords: Demographic; Multilevel Analysis; Multilevel Regression Analysis Model; Statistically Significant, Intra-Class Correlation;

INTRODUCTION

Multilevel models are statistical models that analyze data with multiple levels of organization, such as students within schools or individuals within communities. They are also known as hierarchical linear models, linear mixed-effects models, mixed models, nested data models, random coefficient models, random-effects models, or split-plot designs (Cohen 2003).

The fertility rate of a country significantly impacts its population size, structure, and composition. Nigeria, as one of the world's most populous nations, has a substantial fertility rate. According to the Nigeria Demographic and Health Survey of 2013, fertility is a key factor in population dynamics. In 2018, Nigeria's population exceeded 180 million, making it the seventh most populous country globally (Obiyan et al., 2019). The recent Nigeria Demographic and Health Survey (NDHS) data underscored the persistent high total fertility rate (TFR) per woman in Sub-Saharan Africa, particularly in the southern region. This trend, as documented by Oyinlola et al. (2017), has remained relatively unchanged over time. Multilevel modeling, a statistical technique specifically designed for analyzing hierarchical or clustered data, is indispensable for understanding such complex data structures. Examples of clustered data include educational research (students nested within schools), family studies (children nested within families), medical research (patients nested within physicians or hospitals), and biomedical research (teeth nested within individuals). While other regions like Asia, Latin America, and North Africa have witnessed significant fertility decline, the transition in Sub-Saharan Africa has been slower and less pronounced. Most research on fertility change has concentrated on countries that have already achieved substantial fertility reduction or are undergoing rapid transition. However, several countries, particularly in the central and western Sahel, continue to grapple with high fertility levels. Niger, Chad, and Mali, located in this region, rank among the top five countries globally in terms of TFR (UNPD, 2019). Even in the Sahel, fertility decline has been either slow or stalled, indicating the ongoing challenges in reducing fertility rates in these regions. The persistent high fertility rates in Sub-Saharan Africa have far-reaching implications for population growth, economic development, and social well-being. Addressing these challenges requires a multifaceted approach that includes improving access to education, healthcare, and family planning services, as well as implementing policies that promote gender equality and empower women.

With the limited fertility change in the Sahel, most demographic studies have concentrated on the implications of impending population growth and identified social, cultural, and political obstacles to fertility decline (Groit and May, 2017). These studies have primarily focused on the level of fertility, using the total fertility rate and its proximate determinants, such as early marriage, low contraceptive use, and low status of women (Hertrich, 2017; Tab Utin and Schoumaker, 2004). Surprisingly, few studies have explored whether underlying changes are occurring beneath the seemingly stable aggregate fertility measure (Spourenberg and Issaka, 2018).

This is particularly perplexing considering the acknowledged importance of fertility in determining future population size. A long-standing and unresolved debate exists among historical demographers regarding whether the historical fertility transition was primarily driven by spacing (increasing the time between births) or by stopping (terminating childbearing at a younger age). Additionally, there is little consensus on the relative importance of gender relations in influencing reproductive change. During the 19th and early 20th centuries, most European societies underwent the fertility transition, shifting from high to low fertility. This transition has been the subject of a long-standing and unresolved debate among historical demographers.

MATERIALS AND METHODS

Multilevel models (Also known as hierarchical linear models, linear mixed –effect, mixed model, nested data models, random coefficient, random-effect models, or split –plot designs) are statistical model of parameter that vary at more than one level (Cohen, 2003). Multilevel model have been used in education research or geographical research, to estimate separately the variance between populations within the same region.

The Multilevel Regression model is known on the research literature under variety of names, such as 'Random Co-efficient Model' (De leeuw and Kreft, 1986: Longford, 1993), Variance component model' (Longford, 1993) and hierarchical linear model (Raudenbush and Bryk, 1986; Bryk and Raudenbush, 1992). It assumes hierarchical data, with one response variable measured at the lowest level and explanatory variable at all exiting level. Conceptually the model is often viewed as a hierarchical system of regression equation. For example assume we have data in J group or contexts,

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and a different number of individual N_j in each group on the individual (lowest) level we have the dependent variable Y_v and the explanatory variable X_{ij} and on the group level we have explanatory variable Z_j. Thus, we have a separate regression equation in each group;

$$Y_{ij} = \beta_{oj} + \beta_{ij}X_{ij} + \varepsilon_{ij} \quad (1)$$

The β are modelled by Explanatory variable at the group level;

$$\beta_{oi} = Y_{oo} + Y_{oi}Z_j + U_{oj} \quad (2)$$

$$\beta_{ij} = Y_{io} + Y_{ii}Z_j + U_{oj} \quad (3)$$

Substitution of (2) and (3) in (1) gives

$$Y_{ij} = Y_{oo} + Y_{io}X_{oj} + Y_{oi}Z_j + Y_{ii}Z_jX_{ij} + U_{ij}X_{ij} + U_{oj} + \varepsilon_{ij} \quad (4)$$

In general there will be more than one explanatory variable at the lowest and also more than one explanatory variable at the highest level. Assume that we have P explanatory variables X at the lowest level indicated by the subscript $(\beta 1 \ldots P)$ and Q explanatory variables Z at the highest level, indicated by the subscript $(q = 1 \ldots Q)$. Then equation (4) becomes the more general equation;

$$Y_{ij} = Y_{io} + Y_{po}Xpij_{po} + Y_{oq}Z_{qj} + Y_{pq}Z_{qp}X_{pij} + U_{pj}X_{pij} + U_{oj} + \varepsilon_{ij} \quad (5)$$

The estimators generally used in Multilevel Analysis are maximum likelihood Estimator, with standard error from the inverse of the information matrix.

Intra-class Correlation

The Intra-class correlation is then defined as:

$$\rho = \frac{\sigma^2{}_{u0}}{\sigma^2{}_{u0} + \sigma^2_{eij}} \quad (6)$$

Where

$$c = \frac{1 + k_{P0}}{1 - P_0} \quad (7)$$

$$DF_1 = n - 1$$

$$DF_2 = n(k - 2)$$

$$C_0 = \frac{\frac{1 + k_{P0}}{1 - P_0}}{\frac{1 + k_{P1}}{1 - P_1}} \quad (8)$$

The power of this test procedure is given by power:$= 1 - P_{\left(F \geq c_0 F_{1-\frac{\alpha}{2}}, df_1, df_2\right)}$

$$C_0 = \frac{\frac{1 + k_{P0}}{1 - P_0}}{\frac{1 + k_{P1}}{1 - P_1}} \quad (9)$$

The aim of this paper is to assess variability in fertility level across Northern Nigeria and specific objectives are:

i. Modification of the existing Multilevel Regression Analysis model

Compare the existing Multilevel Regression Analysis model results with the modified Multilevel Regression Analysis mode results.

Assess the impact of fixed and random effects on the intercept.

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RESULTS AND DISCUSSION

Proposed modification of the Multilevel regression model

We consider the modification of the random slope of the existing model at the second level equation, modelling certain structure of the underlying categorical covariate in the hierarchical regression, we proceed as follows by taking square root of the coefficients of the variable of the interest the population under study which are Religion, number of Wives, Highest educational level and sex of child respectively;

Thus we have a separate regression equation in each group;

$$Y_{ij} = \beta_{oj} + \beta_{ij}X_{ij} + \varepsilon_{ij} \qquad (10)$$

Modification of the random slope

$$\beta_{oi} = Y_{oo} + Y_{oi}Z_j + U_{oj} \qquad (11)$$

$$\beta_{ij} = Y_{io} + \sqrt{Y_{ii}Z_j + U_{oj}} \qquad (8)$$

Where;

= the coefficient of the variables (predictors of the model) 1, 2, 3, 4

1 = Religion
2 = Number of Wives
3 = Highest Educational levels
4 = Sex of Child

j = Indicate the regions in the multilevel regression 1, 2, 3

1 = North Central
2 = North East
3 = North West

Modification of the slope of the model

Certain operations were performed on the random slops of the model to see its effect on the expected number of children ever born (TCEB) per family in the regions.

Taking the Root of the slop

$$TCEB_{(NC)} = 3.969 - \sqrt{\beta_{1(NC)}(\text{Religion})} + \sqrt{\beta_{2(NC)}(\text{No of wives})} - \sqrt{\beta_{3(NC)}(\text{Highest educational level})} + \sqrt{\beta_{4(NC)}(\text{Sex of child})}$$

$$TCEB_{(NC)} = 3.969 - 0.228(2.62) + 0.707(1.28) - 0.724(1.13) + 0.235(1.51)$$

$$TCEB_{(NC)} = 3.813 \approx 4$$

Taking the root of the slop gives a better estimate for the Total Children Ever Born (TCEB) in all the Regions, as it is very close to average number of children born in all the regions (given in the descriptive statistics table below).

Comparison of the Models

A good strategy for developing a level-one model is to begin by testing the impacts of a minimal set of theoretically important predictors with fixed-slope coefficients, that is, by assuming the effect of each of these individual-level variables is homogeneous across the regions. The level-one model with fixed coefficients is given as:

$$TCEB = \propto_{00} + \propto_{10}(\text{Religion}) + \propto_{20}(\text{No of wives}) + \propto_{30}(\text{Highest educational level}) + \propto_{40}(\text{Sex of child}) + e_{ij} \qquad (12)$$

Where TCEB = Number of Children Ever Born

TCEB=3.969 – 0.064(Religion) + 0.526(Number of wives) – 0.556(Educational Level) + 0.055(Sex of Child) (13)

The level-two model with varying intercept and slops is given as:

$$\beta_{0j} = \propto_{00} + u_{0j} = 3.969 + 0.092_j \quad (28)$$

$$\beta_{1j} = \propto_{10} + u_{1j} = -0.064 + 0.012_j \qquad (29)$$

$\beta_{2j} = \propto_{20} + u_{2j} = 0.525 + 0.025_j$ (30)
$\beta_{3j} = \propto_{30} + u_{3j} = -0.556 + 0.032_j$ (31)
$\beta_{4j} = \propto_{40} + u_{4j} = 0.055 + 0.00_j$ (32)

The level-two model with varying intercept and slop becomes:
TCEB= $\beta_{0j} + \beta_{1j}(\text{Religion}) + \beta_{2j}(\text{No of wives}) + \beta_{3j}(\text{Highest educational level}) + \beta_{4j}(\text{Sex of child})$ (33)
Using the level-two model, we estimate the number of Children born in a family in the Regions, fixed intercept assumption.

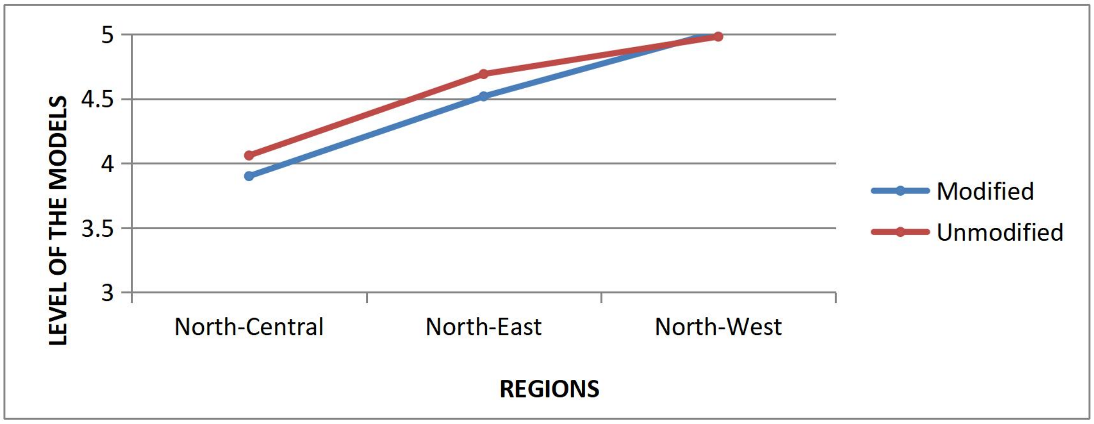

Figure 1: A graph showing the level of variations of the two models.

Fixed and Random Effects

The multilevel regression model assumes that there is a hierarchical data set, often consisting of subjects nested within groups, with one single outcome or response variable that is measured at the lowest level, and explanatory variables at all existing levels. The multilevel regression model can be extended by adding an extra level for multiple outcome variables, while multilevel structural equation models are fully multivariate at all levels. First, with multilevel regression there are at least two levels and two models. The independent variables in a level-one model are also substantively conventional. Along with the intercept, they include obvious level-one measures such as race, gender etc. One or more of these measures, however, may have a coefficient with a random component as well as a fixed component. At level two, however, the dependent variables are random components of regression coefficients. Each random component, whether an intercept or a slope, has its own equation. Explanatory factors for random components are substantively conventional measure.

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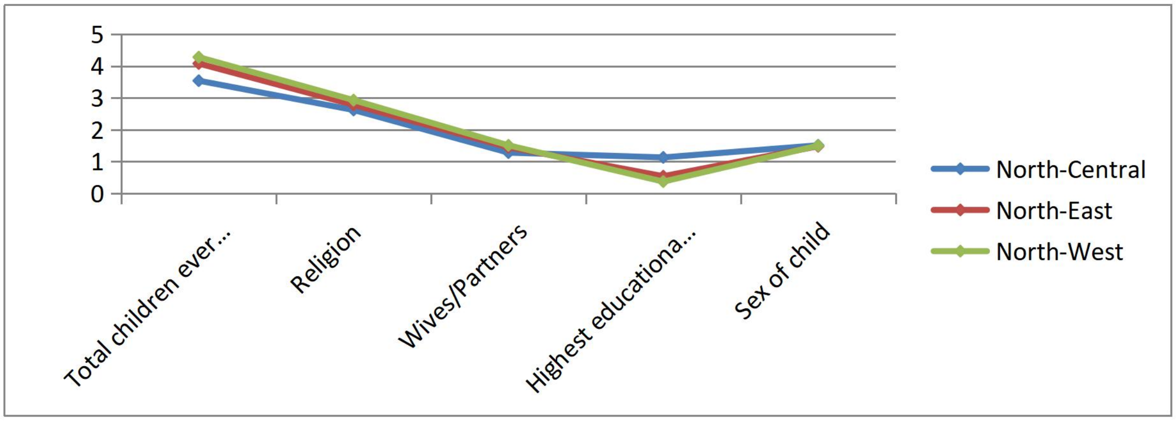

Figure 2: A graph showing the obtained mean for each variable across the regions.

Table 1: Tests of Fixed Effects

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	5273.170	636.554	.000
Education	1	4524.264	87.278	.000
Religion	1	5273.136	3.807	.051
Sex_of_child	1	5273.546	.066	.798
No_of_wives	1	7.040	30.571	.001

a. significant at 0.05

b. Dependent Variable: Total children ever born.

Table 2: Estimates of Fixed Effects

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	3.618245	.143410	5273.170	25.230	.000	3.337101	3.899388
Education	-.376284	.040278	4524.264	-9.342	.000	-.455248	-.297321
Religion	-.028613	.014665	5273.136	-1.951	.051	-.057363	.000137
Sex_of_child	.017123	.066733	5273.546	.257	.798	-.113702	.147947
No_of_wives	.460815	.083343	7.040	5.529	.001	.263967	.657663

a. Region = North

b. Dependent Variable: Total children ever born.

Table 3: Case Processing Summary

	Label	Count	Marginal

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				Percentage
Region	1	North Central	1264	23.96%
	2	North East	1520	28.81%
	3	North West	2492	47.23%
Valid			5276	100%
Excluded			673	
Total			5949	

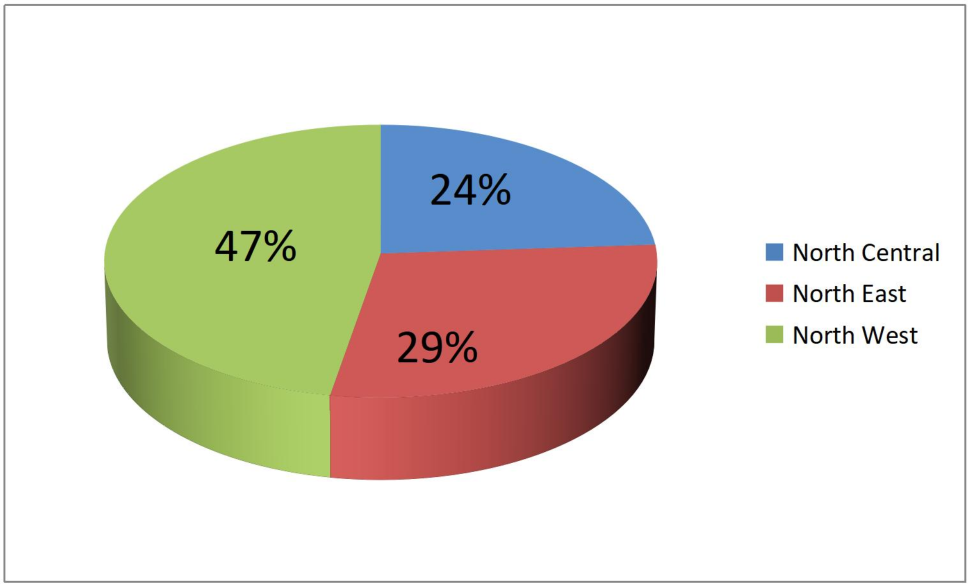

Figure 3: A graph showing the marginal percentage across the regions.

CONCLUSION

In this work, we modified the Multilevel Regression Analysis model by taking the root of the slope of the existing Multilevel Regression Analysis model. The modified model was then compared with the existing Multilevel Regression Analysis model and it was discovered that the modified Multilevel Regression Analysis model gave a better estimate of the Total Children Ever Born (TCEB) across the three (3) geopolitical zones in Northern Nigeria (North-Central, North-East and North-West). The Multilevel Regression Analysis model was fit to assess the Fixed and Random effects on the intercept to describe the relationship between the total number of children ever born and four (4) independent Variables (Religion, Highest Educational Level, Number of Wives, and Sex of child) across the regions. The fixed component estimate shows that the contextual variables (Number of wives and highest educational level) both have statistical significant coefficients. Number of children born to individual families on average, decline as educational level increases, but also, children born actually increases on average, as the number of wives increases.

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The random intercept β_{oj} takes the position of a dependent variable in a simple regression equation. The objective of the equation is to account for region variability in the random intercept and was also discover that the Intra-Class Correlation (ICC) was not statistically significant because the covariance parameter was redundant.

Policymakers should prioritize female education, as higher educational levels lead to lower fertility rates. Expanding scholarships, conditional cash transfers, and awareness campaigns can empower women and reduce birth rates over time. Strengthening family planning programs is also essential, particularly in polygamous households, by improving access to contraception and reproductive health services. Integrating these services into schools and community health centers will enhance their reach and effectiveness.

Women's empowerment initiatives, such as job creation and economic programs, can further influence family size decisions. Policies that improve healthcare access, legal rights, and social services for women will help them make informed reproductive choices. Additionally, comprehensive sexuality education in schools will equip young people with knowledge about family planning, supporting a culture of informed decision-making.

Family planning and education programs should work together to ensure that communities understand and utilize reproductive health services. Regional policies should consider cultural and socioeconomic differences, focusing on education, contraception, and economic empowerment. A holistic approach will improve family well-being and support sustainable population management across Northern Nigeria.

Lastly, this study recommends the modified Multilevel Regression Analysis model should be used for estimation of hierarchical data set or nested data.

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