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BAYESIAN SEMIPARAMETRIC MODELLING OF DETERMINANTS OF STUNTING IN NIGERIA

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ABSTRACT

The effect of childhood malnutrition varies across geographical location in any given country. Studies on childhood malnutrition without geographic information mask the spatial effect. This study explores the spatial effect and the determinants of stunting in Nigeria.
Using the 2013 Nigerian Demographic Health Survey (NDHS) data, we specified a model that simultaneously measures the fixed effect of categorical covariates, nonlinear effect of continuous variable, spatial effect and random effect of the community and households using the diffuse prior, the P-spline with second-order random walk, Markov random field prior and the exchangeable normal priors respectively. The dependent variable was specified as 1 if a child under five years (U5) is stunted and 0 otherwise. The logistic distribution was used to capture the binomial distribution of the dependent variable; the choices of hyperparameters were varied to check for the sensitivity of the priors on the posterior distribution. Using estimation criterion: Odd Ratio (OR) and Confidence Interval (CI), North East (OR: 1.5232, CI: 1.7160, 2.0431) and North West (OR: 1.0241, CI: 1.0542, 1.1645) show that the North Eastern and Western regions account more for stunted children in Nigeria. Secondary (OR: 0.8126, CI: 0.7344, 0.8511), higher (OR: 0.7279, CI: 0.5475, 0.7440) explain significant lower odds of U5 who are stunted with women who are educated. Also, stunting of the children under five of women in states like Rivers, Bayelsa, Delta, Edo, and Enugu are likely to be less compare to the children under five in Kebbi, Sokoto, Zamfara , Kaduna, Kano, Lagos and Jigawa. The posterior distributions are less sensitive to variations in the choices of priors. The ameliorating measures should channeled towards the affected regions in the country which are the North Eastern and Western regions

Keywords: Binomial, Geo additive model, Nigeria, Prior, Posterior, Stunting.

INTRODUCTION

Childhood malnutrition being one of serious health issues facing developing countries, especially Nigeria, is an indicator of well-being, which is also associated with morbidity, mortality, impaired childhood development and reduced labour productivity (Adebayo 2004).

Many applications have been explored in spatial epidemiology, some include, Fahermeir, Khatab (2008), Lawson (2008), Lawson, Biggeri and Williams (1999) providing detailed discussions. The major element is the assessment of patterns of relative disease risk in terms of possible clustering, perhaps around environmental point sources. Lawson (2008), Anselin and Florax (2002) have provided long standing tradition spatial modelling which have been further reviewed to include the Bayesian principles. In application to some public health cases, the geo-additive model has been extensively used in estimating or analysing different situations, which include family planning, childhood diseases and nutritional status, maternal mortality etc. (Fahrmeir and Lang, 2001, Fahrmeir, Kneib and Lang 2004).

Malnutrition often begins at conception which is linked to poverty, low levels of education, and poor access to health services; which include reproductive health and family planning. (UNICEF (2000), Klasen, (1999), Nyovani, Matthews and Margetts, (1999). According to reports from World Health Organisation (2014), it was estimated that 60% of the 10.9 million annual deaths among children younger than five years old in low-income and middle-income countries are directly associated with malnutrition. Children deserve good care, nutrition and health which encourage their social, emotional, physical and intellectual growth. Nutritional deficiencies contribute to the high rates of disability, morbidity, and mortality in Nigeria, especially among infants and young children with several data suggesting a crisis in the nutrition situation of the country, (Ojofeitimi, 2005). Urgent intervention is therefore necessary for an enabling environment through well-articulated policies, projects, and programmes/interventions to ensure wholesome development of Nigerian children and to enhance their quality of life. Numerous regional surveys portray a sorry state of nutrition in Nigeria. The nutritional status of children is usually quantified in terms of anthropometrical measures like weight-for-age (underweight), height-for-age (stunting) or weight-for-height (wasting). In adults, nutritional status is commonly expressed as the Body Mass Index (BMI).

Stunting is generally used as an indicator of long-term chronic nutritional deficiency. Child stunting has been extensively studied in developing countries, including Bangladesh, Brazil, Indonesia, Kenya and Mozambique. Malnutrition in children is the consequences of a range of factors which can be grouped as food intake, environmental and health factor. Rao, Ladusingh and Pritamijt, (2004) explained that the consequences of this range of factors are often related to insufficient food intake, poor quality of food, severe and repeated bouts of infections and poor nutritional child practices such as delayed breastfeeding in spite of good food supplementation. The underlying responsible factors are households, food insecurity, inadequate preventive and curative health services and insufficient knowledge of proper care (Measham, 1999). Poor maternal and demographic situations, poor socioeconomic conditions, poor feeding and immunization practices and regional differentials are the most important factors associated with the high prevalence of severe and moderate stunting among preschool children in various regions of Bangladesh (Rahman and Chowdhury, 2007).

Reduction of child malnutrition is one of the problems that need to be addressed in Nigeria. The federal government has been aggressive on exclusive breast feeding for the first six months of delivery of a baby. Nigeria ranked second among the nations in sub Saharan Africa with malnourished children and it was also observed that malnutrition in Nigeria is a concentrated phenomenon, a relatively small number of states, districts, and villages accounted for a large share of the burden of malnutrition. In Nigeria, with one of the highest percentage of undernourished children in the world, the situation is dire (Ladusingh, Yadav, Gayawan, 2014). The consequence of child malnutrition on morbidity and mortality are enormous and there is, in addition, an appropriate impact of under-nutrition on productivity so that a failure to invest in combating nutrition reduces potential economic growth, (Ladusingh, Yadav and Gayawan , 2014,

Adebayo, 2003, Manuel, Tatyana, Stephen, and Stefan, 2012), studied some of the risk factors associated with acute or chronic undernutrition. The NDHS data follows a three-stage stratified design in which the observations in the same cluster may be correlated due to exposure to a wide range of common factors, (Kazambe 2009, Alaba, 2015). This may explain similar pattern in the same community, which may vary from one community to the other. (Ent wisle and Alexander, 1989). However, these factors may be quantified; hence the need for latent variables to allow for unobserved covariates. This latent structure is then modeled as random effect; factors that influence chronic undernutrition which are interrelated and spread over space. Boundaries that are contiguous are likely to display similar undernutrition pattern which will give rise to spatial autocorrelation. Therefore, the latent random effect can be extended to permit both spatially structured variation and unstructured heterogeneity. Various studies assume the Markov random field model for the spatially structured pattern and an exchangeable Gaussian model for the unstructured heterogeneity (Besag, Green, Higdon and Mengersen, 1995). A flexible model is needful to estimate the effect of continuous variables, (Lang and Brezger, 2004). Variables such as age, Body Mass Index (BMI) enter the model non-parametrically without specifying the form of the relationship. (Ladusingh, Yadav and Gayawan, 2014). This model explored the factors associated with child stunting for children under the age of five taking cognizance of the fixed effect, nonlinear, spatial and unobserved heterogeneity which have not been captured before. Most of these studies focused on regression analyses of anthropometric measure of nutritional status such as stunting, wasting or underweight, neglecting unobserved variable or heterogeneity and spatial effect. A geo-additive model extends generalized linear and additive regression in a semiparametric fashion to simultaneously incorporate linear and non-linear nonparametric effects of usual covariates, nonlinear interactions among them, and spatial effects into a geo-additive predictor, (Olubiyi and Olubusoye, 2013)

Geo-Additive Model

Consider geo-additive model specified as

$$\eta_r = f_1\left(x_{r1}\right)+\ldots+f_k\left(x_{rk}\right)+f_{spat}\left(s_r\right)+u_r'\gamma+b_g \quad (1)$$

Where η_r is the geo-additive predictor

$f_{i,i=1,\ldots,k}$ is the nonlinear effect of metrical or continuous covariates $f(spat)$ is the spatially correlated effect of location s_r

u is the fixed effect of categorical variables γ

$b_g, g \in \{1,\ldots.,G\}$ are uncorrelated (unstructured) random effects to model unobserved heterogeneity

For the continuous/metrical covariates, we assume Penalized Splines (P-spline) prior with second order random walk.

$$f(x) = \sum_{t=1}^{k} \alpha_t B_t(x) \quad (2)$$

where

$B_t(x)$ are B-splines, α_t are defined to follow a first order or second order random walk prior. The second order random walk is given as

$$\alpha_t = 2\alpha_{t-1} - \alpha_{t-2} + \varepsilon_t \quad (3)$$

with Gaussian errors $\varepsilon_t \sim N(0,\tau_\varepsilon^2)$ where τ_ε^2 controls the smoothness of f. This variance is estimated jointly with the coefficients of the basis function by assigning a weakly informative inverse Gamma prior with $\tau_\varepsilon^2 \sim IG(\varepsilon,\varepsilon)$. A suitable choice of diffuse prior is assumed for the fixed effect of categorical covariates given as

$$p(\gamma)\alpha\ const \quad (4)$$

The spatial effects follow Markov random field priors.

$$\left\{f_{spat}(s_r) \mid f_{spat}(t); t \neq i, \tau_s^2\right\} \sim N\left(\sum_{t\in\partial_i}\frac{f_{str}(t)}{N_i}, \frac{\tau_s^2}{N_i}\right) \quad (5)$$

where

N_i is the sum of adjacent sites

τ_s^2 is the spatial variance which controls the spatial smoothness

The random effects b_g were modelled from exchangeable normal priors, $b_{ij} \sim N(0,\tau_b^2)$

where τ_b^2 is the variance that accounts for overdispersion and heterogeneity. We assigned highly dispersed but proper prior for all variance components. An inverse Gamma distribution with hyperparameters *a* and *b* is chosen, such that $\tau^2 \sim$ IG(*a*,*b*). Standard choices of hyperparameters are *a*=1 and *b*=0.005 or *a*=*b*=0.001(which is close to Jeffrey's noninformative prior. (Fahrmeir and Lang 2001, Kazembe, 2009). These values can be varied to examine the sensitivity of the choices of hyperparameters to the inverse Gamma distribution.

Letting α = (f, f_{spat}) , τ to represent the vector of all variance components, and β is the vector of fixed effects parameters, then the posterior probability distribution is given as

$$p(\alpha,\tau,\beta \mid y) \;\alpha\; p(y \mid \alpha,\beta,\tau)p(\alpha)p(\beta)p(\tau) \quad (6)$$

where

p(y|α, τ, β) is the likelihood function of the data given the parameters of the model (based on the dependent variable) $p(\alpha)p(\beta)p(\tau)$ are the prior densities of all the parameters

The Bayesian framework based on Markov Chain Monte Carlo (MCMC) simulation techniques from full conditionals for nonlinear, spatial, fixed effects and smoothing parameters will be used for the posterior analysis. The Deviance Information Criterion (DIC) is employed for comparison of the models.

The DIC is defined as

$$DIC = \bar{D}(\theta) + pD \quad (7)$$

where

$\bar{D}$ is the posterior mean of the deviance

pD is the effective number of parameters (not equal to degrees of freedom)

Small values of $\bar{D}$ and pD indicate a better and parsimonious model respectively. The model with the lowest DIC is the best.

MATERIALS AND METHODS

Data

The study followed both quantitative and cross-sectional study of children U5 years using 2013 NDHS data. The 2013 NDHS was conducted by the National Population Commission (NPC) with funding support from United State Agency for International Development (USAID), the United Nations Population Fund (UNFPA), and the United Kingdom Department for International Development (DFID). Technical support was provided by ICF International. The 2013 NDHS sample was selected using a three-stage stratified design consisting of 904 clusters, 372 urban areas and 532 in rural areas. In the 2013 NDHS dataset, 40,320 households were selected out of which 38,522 were interviewed. In the selected households, 39,902 women in the childbearing age (15 – 49years) were found eligible for the interview. This study is based on the survey data with all participant identifier removed. We focused on children who had chronic malnutrition (insufficient height for age). The socio-economic variables used as explanatory variable in explaining U5 stunting are: child's age, mother's age at birth, BMI, educational attainment, ethnicity, religion, place of residence, place of delivery, wealth index, work status, region. *Age* is an indispensable demographic tool which was included as a measure of expected height of a child. *Educational attainment* captures the effect of knowledge on how the mothers feed their wards in any community. *Place of residence* is linked to urbanization and modernization. *Region* explains the difference in location of the respondents which is characterized by different culture and different feeding habit. *Mother's age at birth* is a factor that should explain level of maturity and experience on child care.

Model Specification

We specified stunting as a binary logit model. The binary indicator is defined

$$y_{ij} = \begin{cases} 1\, if\ a\ child\ is\ stunted \\ 0\ otherwise \end{cases}$$

$$y_{ij} / \gamma, b_i \sim Bin(n_i, \pi_i)$$

$$\eta_i = w'\gamma + f'x + f\left(spat\right) + b_i \quad (8)$$

where

η_i is the average number of children who are stunted

$w'\gamma$ is the vector of fixed effect of the categorical covariates.

$f'x$ is the vector of unknown smooth functions of continuous and nonlinear covariates

$f(spat)$ is the spatial effect

b_i is the community effect

We considered four models to investigate factors associated with child stunting using variants of (8). In the first model (M1), all the effect of the categorical covariates, continuous covariate effects were estimated linearly. In the second model (M2), we included the spatial effect to identify the states with strong spatial pattern for stunting. In the third model (M3), we introduced unobserved random effects of community while (M4) explains the linear effect of the categorical variables, the nonlinear effect of continuous variables, the spatial effect and the unobserved random community effect.

Table 1: Summary of Diagnostic Accuracy of the Four Models

Model	$\bar{D}$	pD	**DIC**
M1:All variables fixed	19552.065	32.538	19630.435
M2: All variables fixed + spatial effect	18949.638	60.615	19123.624
M3: All variables fixed + spatial + community effect	17440.522	501.270	18205.515
M4: All categorical fixed + spatial + nonlinear of continuous variable + community effect	17110.612	514.822	18076.332

$\bar{D}$ is the posterior mean of the deviance, pD is the effective number of parameters, DIC is the deviance information criterion

The four models were implemented in BayesX version 2.1., Besag and Kooperberg (1995). We carried out 20,000 iterations with the first 2000 considered as a burn-in sample. We thinned every 10th iteration of the remaining 18,000 used for parameter estimation. Convergence and mixing were monitored through plotting and estimation of sampling paths and autocorrelation. Sensitivity analysis was carried out by varying the hyperparameters.

The different choices of hyperparameters considered using four alternative specifications of different degrees of uncertainty of following combinations were a = 0.5, b = 0.0005, a = 1 and *b* = 0.005, *a* = *b* = 0.001,and *a* = *b* = 0.005. The first specification was suggested by Kelsall and Wakefield (1998), while the second alternative was proposed by Spiegelhalter, (Best, Carlin and Van der line 2002). The remaining prior with equal scale and shape parameters has often been used as standard choices on the variance of random effect (Brezger et. al, 2002). We discovered that the results were less sensitive to variation of the choices of the hyperparameters.

RESULTS

Table 2: Posterior estimates of stunting using (M4) within 95% Credible Interval (CI)

Variable	**OR**	**SD**	**95%Cl**
Constant	6.1001	0.1534	(5.0112, 9.8653)
Region			
North Central (Ref.)	1.0000		
North East	1.5232	0.0541	(1.7160, 2.0043)
North West	1.0241	0.0617	(1.0542, 1.1645)
South East	0.7561	0.0576	(0.7412, 0.9835)
South South	0.7301	0.0458	(0.6234, 0.7836)
South West	0.8376	0.0672	(0.7867, 0.9241)
Place of Residence			
Urban (Ref.)	1.0000		
Rural	0.9160	0.0120	(0.8762, 0.9202)
Educational attainment			
No education (Ref.)	1.0000		
Primary	1.0334	0.0248	(0.7682, 1.1324)
Secondary	0.8126	0.0431	(0.7344, 0.8511)
Higher	0.7279	0.0445	(0.5475, 0.7440)
Ethnicity			
Other ethnic groups (Ref.)	1.0000		
Yoruba	0.5021	0.0452	(0.4507, 0.5569)
Ibo	0.7425	0.0565	(0.6254, 0.8761)
Hausa	1.6702	0.0687	(1.3410, 2.1541)
Wealth index			
Poorest/poorer (Ref.)	1.0000		
Middle class	0.8192	0.04315	(0.8306, 1.0405)
Richer/richest	0.6718	0.04214	(0.6715, 0.7142)

Religion			
none/traditional (Ref.)	1.0000		
Christianity	0.7001	0.0602	(0.5052, 0.8331)
Islam	1.0345	0.0702	(0.8106, 1.0542)
Mother's Working status			
Not working (Ref.)	1.0000		
Working	0.9820	0.0431	(0.9405, 1.0051)
Place of delivery			
Home (Ref.)	1.0000		
Public hospital	0.9341	0.0324	(0.8915, 0.9256)
Private hospital	0.8344	0.0230	(0.7105, 0.9002)
Continuous/material covariates			
Mother's Current age	0.9613	0.0212	(0.9718, 0.9886)
Body mass index	0.9911	0.0032	(0.9583, 0.9993)
Random component			
Community	1.6733	0.0507	(1.5046, 1.8262)
Spatial component			
States	8.0822	0.5391	(2.5410, 27.5262)

SD- Standard Deviation OR- Odd ratio

From table 2 above, the posterior estimates and 95% CI of our logistic regression model (M4) showed that the South East (OR: 0.7561, CI: 0.7412, 0.9835) children under the age of five are 24% less likely to be stunted compared with the North Central region. The South South (OR: 0.7301, CI: 0.6234, 0.7836) and South West (OR: 0.8376, CI: 0.7867, 0.9241) are 27% and 16% less likely to be associated with stunted children than the North Central region. The credible intervals for the South Eastern, South South and South Western region show a significant lower association with the children under age five being malnourished. North East (OR: 1.5232, CI: 1.7160, 2.0431) and North West (OR: 1.0241, CI: 1.0542, 1.1645) regions are more likely to give an 52% and 2% significant increase in stunted children than the North Central region. The North Eastern and Western regions seems to account for more number of stunted children in Nigeria.

There is about 8% likelihood that the children who reside in the urban areas (OR: 0.9160, CI: 0.8762, 0.9102) are less likely to be malnourished than the children who reside in rural areas. The children of women in the middle class wealth quintile [OR: 0.8192, CI: 0.8306, 1.0405] are 17% less likely to be associated with child's stunting than the children of the women in the poorer or poorest wealth quintile. Similarly, the richest or richer wealth quintiles are 23% significantly less likely to have their children stunted. [OR: 0.6718, CI: 0.6715, 0.7142]. The posterior estimates for women with secondary and higher education are (OR: 0.8126, CI: 0.7344, 0.8511) and (OR: 0.7279, CI: 0.5475, 0.7440) respectively.

As the level of education of a woman increase, so there is a reduction in having a stunted child compared with women with no education. Women with primary education (OR: 1.0334, CI: 0.7682, 1.1324) are 3% more likely to increase having a malnourished child than women with no primary education. This suggests that women with higher education are better exposed and more informed than women with no education who have no understanding of nutritional diet.

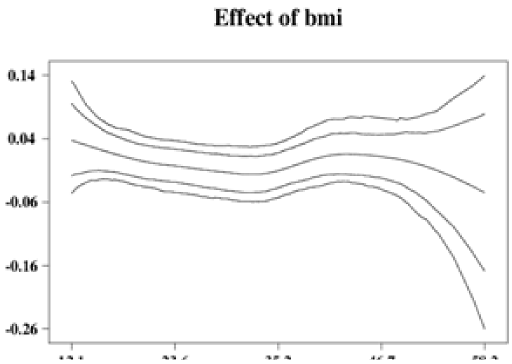

Figure 1: Nonlinear effect of mother's BMI on stunting at 95% CI

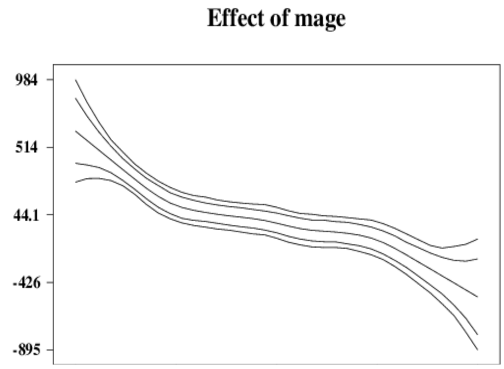

Figure 2: Nonlinear effect of mother's age on stunting at 95% CI

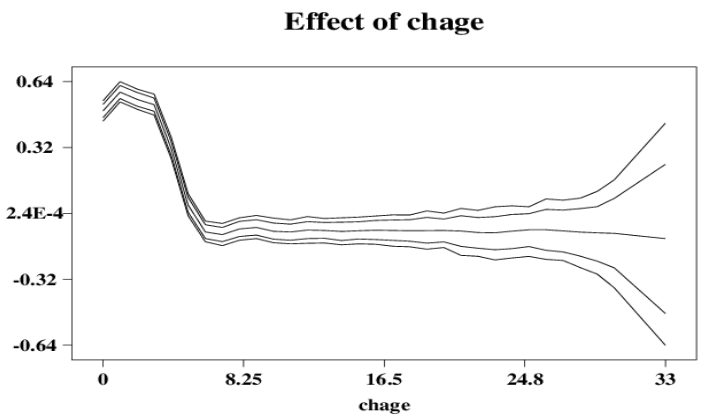

Figure 3: Nonlinear effect of child's age on stunting at 95% CI.

The 95% CI of the nonlinear effects of Mother's BMI, Mother's age and child's age on child's stunting are given in Figures 1, 2, and 3 respectively. Figure 1 shows an inverse relationship of child's stunting BMI. Women with lower BMI have stunted children more than women with higher BMI. The younger women are likely to be associated with child's stunting, however in Figure 2, it was noticed that there is a gradual decline in number of women who's their children under five years of age are stunted from age group 20 and above, while fig. iii indicates a drastic reduction in stunting as the age of the increases. The posterior mean is given in Figure 4 while the 95% CI for the significance of the spatial effect is reported in Figure 5, states with black colour are significantly associated with increase in child's stunting; those in white are associated with lower level of child's stunting while the grey colour are insignificantly associated with stunting. The under five children of women in Rivers, Bayesa, Delta, Edo, and Enugu are likely to be less stunted more than children in Kebbi, Sokoto, Zamfara , Kaduna, Kano, Lagos and Jigawa. Child's stunting is insignificant in all other states.

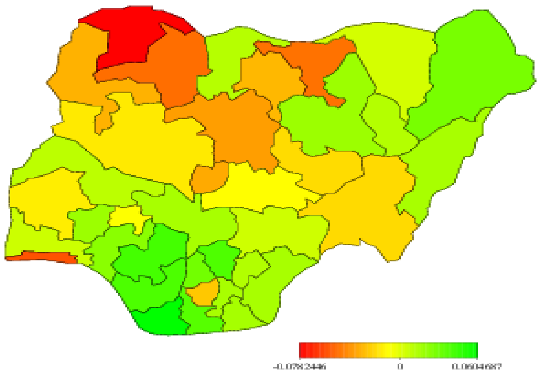

Figure 4

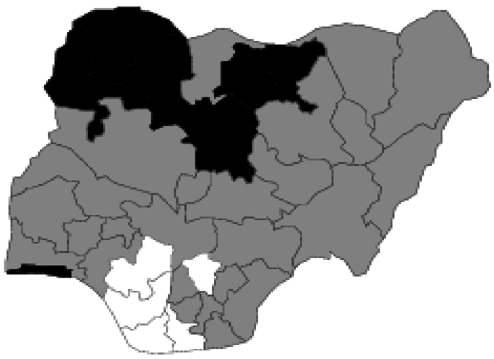

Figure 5

Figures 4 and 5: Posterior estimate of mean and spatial pattern of stunting in Nigeria at 95 % CI.

DISCUSSION

The geo-additive model was used to investigate the spatial effect and the factors determining child stunting in Nigeria. We used a logit link model for the response variable of whether a child under five years of age is height-for-age deficient (stunted) or not by using the 2013 Nigerian Demographic Health Survey (NDHS) data. The diffuse prior was used for the fixed effect of categorical variables, penalized spline with second random walk for the continuous variables, spatial effects followed Markov random field priors while the exchangeable normal priors were used for the random effect of the household and community. Four models (M1-M4) were implemented in BayesX software. M4 gave the least DIC, hence the best fit. The Bayesian framework based on Markov Chain Monte Carlo (MCMC) simulation techniques from full conditional was used for estimation of the unknown posterior distribution. The states in the North Western region and some states of Southern region are more likely to be associated with nutritional problem (stunting) in Nigeria. Stunting appears to worsen until a child is about 24-33 months old and then stabilise at a low level equilibrium. It was also deduced that child stunting was associated with the child's sex and age, type of birth, maternal height, maternal body mass index, previous birth intervals, number of household members, household wealth index score, access to improved sanitation facilities, presence of diarrhoea, parents' education, maternal tobacco use and mother's birth. Results of the categorical covariates have shown that children of women residing in urban areas were more disposed to child stunting than their counterparts in rural areas. Women with lower BMI have stunted children more than women with higher BMI. The younger women are likely to be associated with child's stunting, it was deduced that there is a gradual decline in number of women who's their children under five years of age are stunted from age group 20 and above and a drastic reduction in stunting as the age of the increases. Women residing in rural areas in most developing countries often have less access to reproductive healthcare services than the urban dwellers has, apart from inadequate health facilities, non-availability of health workers who were to enlighten them on importance of exclusive breastfeeding between 0 to 6 months of birth of a new baby is another major factor. (National Population Commission, 2008).

There also appears to be an interaction between mother's education and age, with mother's education having an increasing impact on stunting among older children, this indicates a nonlinear declining trend of child's stunting with the increase in the child's age and increasing trends with mother's age at birth. The nonlinear effect of mother's age at birth on stunting and child's age on stunting demonstrated that the demographic relationships may not always be linear. The fixed effects show the importance of mother's education, wealth index, employment status, residence, and the sex of the child on chronic under-nutrition (stunting). It was deduced that women with higher education are better exposed and more informed than women with no education who have no understanding of nutritional diet. From the results, stunting of the children under five of women in Rivers, Bayesa, Delta, Edo, and Enugu are likely to be less compare to the children under five in Kebbi, Sokoto, Zamfara , Kaduna, Kano, Lagos and Jigawa. Child's stunting is insignificant in all other states in Nigeria.

In conclusion, findings from this study assist in understanding spatial patterns and determinants of child stunting in Nigeria. It is hoped that this will assist in policy development and planning, resource allocation, implementation, monitoring and evaluation since children of today are future leaders of tomorrow. Effective campaigns for mothers of childbearing age and general public on the importance of breast milk and giving a balance diet to their wards is imminent coupled with the government efforts to ensure that care at the health institutions meet required standards and quality. This is very crucial in all states of the Federation since the residual spatial variations show significant high level of child stunting in a few states.

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Competing Interests: None

Ethical Approval: Not required

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