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Stepwise Geoadditive Modelling of the Ideal Family Size in Nigeria

Nijerya'da İdeal Aile Büyüklüğünün Aşamalı Jeotoplamsal Modellemesi

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ABSTRACT Objective: Family size substantially contributes to an improved child and maternal well-being and economic growth of a nation. In this paper, we aim at determining possible determinants of ideal or preferred family size as desired by married women in Nigeria. **Material and Methods:** An extracted dataset from the 2013 Nigeria Demographic Health Survey were analysed using a Bayesian stepwise approach that involves simultaneous selection of variables and smoothing parameters. The model is geo-additive - it allows for geographical variations at a micro level of states, as well as both linear and nonlinear effects of variables to be investigated. Within a Bayesian context, we assigned appropriate priors on all the parameters and functions. **Results:** Findings reveal that substantial geographical variations in the preference of family size exist across the states. Further, the results from the spatial analysis showed that married women from the Northern states have the desire for more children, as compared to their southern counterparts. Respondent's level of education, type of marital union, sex of household head, age, wealth index, religion, working status, and the number of siblings are significantly associated with their ideal family size. Mother's age at first birth is significantly non-linearly related to the ideal family size. **Conclusion:** Government and policymakers need to pay attention to findings from this study, as it can help in designing better strategies that will enable the attainment of the Millenium Development Goals that are firmly related to fertility and family sizes.

Keywords: Geoadditive models; spatial analysis; stepwise regression; Bayesian inference; Family size

ÖZET Amaç: Aile büyüklüğü, gelişmiş bir çocuk ve anne refahına ve bir ulusun ekonomik büyümesine büyük ölçüde katkıda bulunur. Bu makalede Nijerya'da evli kadınlar tarafından istenen ya da tercih edilen aile büyüklüğünün olası etkenlerini belirlemek amaçlanmaktadır. **Gereç ve Yöntemler:** Nijerya Demografik Sağlık Çalışması 2013'ten elde edilen veri seti düzleştirme parametrelerini ve eşzamanlı değişken seçimini içeren aşamalı Bayes yaklaşımı ile analiz edilmiştir. Model jeotoplamsaldır. Bu modelde değişkenlerin hem lineer hem de lineer olmayan etkilerinin araştırılmasının yanı sıra eyaletler arasında coğrafik varyasyonların mikro düzeyde araştırılmasına olanak sağlamaktadır. Bayesian yapısı içinde tüm parametrelere ve fonksiyonlara uygun önsel değerler atanmıştır. **Bulgular:** Bulgular eyaletler arasında aile büyüklüğü tercihinde önemli coğrafi değişikliklerin olduğunu göstermiştir. Ayrıca spatial analizden elde edilen sonuçlara göre güneylilerle karşılaştırıldığında kuzeydeki eyaletlerdeki evli kadınlar daha fazla çocuk sahibi olmak istemektedir. Deneğin eğitim düzeyi, evlilik birliği türü, hane reisinin cinsiyeti, yaş, gelir indeksi, din, çalışma durumu ve kardeş sayısı ideal aile büyüklüğü ile anlamlı olarak ilişkili bulunmuştur. Annenin ilk doğumdaki yaşı ideal aile büyüklüğü ile doğrusal olmayan yönde anlamlı olarak ilişkilidir. **Sonuç:** Aile büyüklüğü ve doğurganlık ile ilişkili olan Bin Yıllık Kalkınma Hedeflerine ulaşılmasını sağlayacak daha iyi stratejiler belirlenmesinde yardımcı olacağı için Hükümet ve politikacılar bu çalışmanın sonuçlarına dikkat etmelidir.

Anahtar Kelimeler: Jeotoplamsal modeller; spatial analiz; aşamalı regresyon; Bayes yaklaşımı; Aile büyüklüğü

Ideal family size is a measure of a person's preferred family size. Similarly, put it differently by referring to ideal family size as the desired number of children in one's lifetime.[1] Family size in Africa has long been a topical issue.[2-4] Precisely, Nigeria, as the most populous country in Africa and one of the fastest population growth rate in the world has been more studied in terms of family size.[5-7] These studies, apart from investigating the determinants of family size, have shown its impact on maternal and child health, economy and the society at large.

Information on ideal family size or fertility preferences considerably aids family planning programs because planners can use it to assess the desired number of children, as well as the extent of unwanted pregnancies. Furthermore, it helps in understanding future reproductive behaviour. Ideal family size is an important indicator of fertility preferences that provides information on the number of children that an individual or married couples desire.[8]

Previous studies investigated family size as a function of fertility level or the number of children given birth to, but in this paper, we focused mainly on the ideal family size, which is a function of mindset and not the actual fertility level.[2, 4-6] Although many studies investigated fertility levels in Nigeria, we are yet to come across any that studied ideal family size or fertility preferences. Additionally, the majority of these studies on fertility levels utilized the traditional Poisson regression model, in which the assumption of linear dependence on the outcome variable, for continuous covariates, have been termed as being too rigid in many real-life applications.[9]

In this study, we adopted a stepwise geo-additive regression model, which simultaneously screens predictor variables and jointly estimate the fixed effects, nonlinear effects of continuous covariates, spatial effects and possible random effects accounting for unobserved heterogeneity.[10] Utilizing the NDHS (Nigeria Demographic Health Survey) data, we explore fertility preferences using the ideal number of children desired by married women in Nigeria.

MATERIAL AND METHODS

DATA

We used the data extracted from NDHS for 2013 (www.measuredhs.com). NDHS data is a nationally representative sample, which provides information on fertility and family planning, as well as demographic and health indicators, for both women and men in the age bracket of 15-49. The survey got an ethical clearance from measuredhs as approved by the ethical committee of ICF Macro (Calverton, MD, USA). Details of this data have been described elsewhere.[11] From the data including 38948 respondents, we selected 23403 married women of childbearing age. Our choice of predictor variables was informed by some social, economic, and demographic variables that have been found from the literature to have an association with family size preference. Description of the variables extracted from the data can be found in Table 1.

The geographical information of the respondents was extracted in the form of a boundary file, which was re-coded to match the 36 states and the Federal Capital Territory (FCT). Nigeria comprises six large geopolitical zones, which are sub-divided into 37 administrative states, as shown in Figure 1.

METHODS

We will briefly describe the structured additive regression (STAR) or geo-additive model used in our analysis. Given that we used a Bayesian setup, the models will additionally be described from a Bayesian perspective.

TABLE 1: Description of variables included in the analysis.

Variables	Description
ideal	Total number of children as desired by the respondent
siblings	Number of siblings of the respondent
urban	Type of locality in which the respondent lives in
edu1	Respondent's level of education
edu2	Husband's level of education
male	Sex of the household head
wealth	Wealth index of the family
working	Respondent's working status
working2	Husband's working status
religion	Religion
polygamy	Type of marital union
motherAge	Age of the respondent
ageBirth	Respondent's age at first birth
marrageBirth	Interval of marriage to first birth (in months)
state	Respondent's state of residence

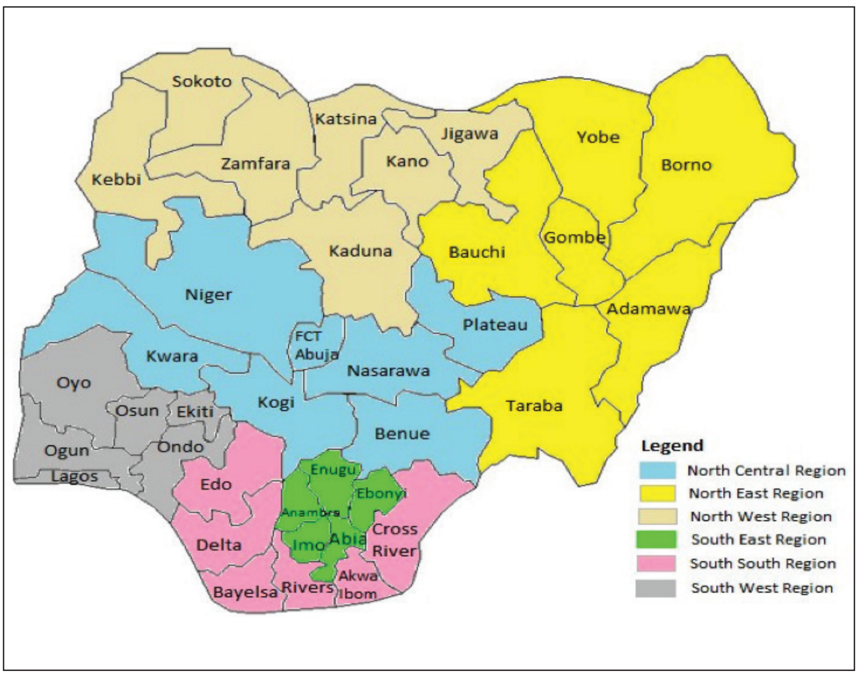

FIGURE 1: Map of Nigeria showing the states of location.

Geo-Additive Model

We assume that there are observations (y_i, v_i, x_i, s_i) indexed i (i =1, . . ., n), where y_i is the ideal family size, assumed to be Poisson distributed; v_i is a vector of categorical covariates; x_i is a vector of continuous covariates; s_i is the state where the *ith* respondent lived at the time of the survey. We adopt the STAR model, which have the following form:

$$\eta_i = v_i'\beta + \Sigma_{j=1}^{p} f_j(x_{ij}) + \Sigma_{k=1}^{K} g_k(x_{ik}, x_{ik'}) + f_{spat}(s_i) \quad (1)$$

Where $\boldsymbol{\beta}$ is a vector of fixed effect parameters; the function f_j are nonlinear smooth functions of the continuous covariates; g_k are the interaction effects of continuous covariates x_{ik} and x'_{ik}; f_{spat} are the spatial effects of location s, and b_i is the unit or individual random effects.

The STAR model above, proposed by, which reflects the focus of methodological research in this study, has its roots from the generalized additive model.[12-14]

Specification of Bayesian Prior Distributions and Hyper-Parameters

As required for Bayesian inference, appropriate priors are assumed for the parameters and functions. Independent diffuse priors are usually assumed on the fixed effects parameters, while the Bayesian P-splines priors are assumed for the non-linear effects.[15,16] The smoothness of function f is achieved by considering first-order Gaussian random walk:

$$\beta_1 = \beta_{j-1} + \in_1 \quad (2)$$

Or second-order random walk:

$$\beta_1 = 2\beta_{j-1} - \beta_{j-2} + \in_1 \quad (3)$$

Where $\boldsymbol{\beta}$ are B-splines, $\in_1$ are i.i.d. errors $\sim$ N $(0, \gamma^2)$. γ^2 controls the smoothness of the function f, and it has a weakly informative and highly dispersed inverse gamma prior which is achieved by choosing hyperparameters a and b that are very small.

For the spatial effects, a Gaussian Markov random field (GMRF) prior, is usually assumed.[17]

$$\text{GMRF: } (f_{spat}(s) / f_{spat}(t);\, t \neq s,\, \gamma^2) \sim N(\Sigma_{t\, \varepsilon \delta_s} f_{spat}(t) / N_s,\, \gamma^2 / N_S) \quad (4)$$

Where N_s is the number of adjacent states of s, and δ_s are the neighbours of state s. γ^2 and the inverse of N_s control the amount of deviation the effect of state s is allowed from its prior expectation. The spatial variance γ^2 also assumes an inverse gamma prior distribution.

Posterior Distribution

If we let $\boldsymbol{\theta} = (f, f_{spat})$ be a vector of non-linear effects parameters, γ to represent the vector of all variance components, and $\boldsymbol{\beta}$ to be the vector of all fixed effects parameters, the posterior distribution will take the form:

$$P(\boldsymbol{\theta}, \gamma, \boldsymbol{\beta}|y) \propto P(y|\boldsymbol{\theta}, \boldsymbol{\beta}, \gamma)\, P(\boldsymbol{\theta})\, P(\boldsymbol{\beta})\, P(\gamma) \quad (5)$$

The posterior distribution in equation (3) is analytically intractable and does not have a closed form. Therefore, MCMC simulations using a Gibbs-sampling algorithm are usually employed to estimate the unknown posterior distribution. See the work of for full details about Bayesian inference and MCMC.[12]

DATA ANALYSIS

We explored the response variable, the desired family size, using its summary statistics and histogram. In fitting the STAR model in equation (1), given that the decision as to which of the covariates enter the model, whether continuous covariates enter linearly or nonlinearly, as well as possible interactions of the continuous covariates, are often challenging to make apriori, we adopted the Bayesian stepwise regression. This stepwise regression procedure, proposed by, performs variable selection and estimates parameter effects simultaneously.[10] Inference at this model selection stage is based on a penalized likelihood approach for estimating the STAR model, to minimize the AICc – the goodness of fit measure. MCMC algorithms are partly used for computing the interval estimates.

Given the response variable $y_i \sim \text{Poisson}(\mu_i)$, the following equation is fitted:

$$\mu_i = v_i{}'\beta + \Sigma_{j=1}^{P} f_j(x_{ij}) + \Sigma_{k=1}^{K} g_k(x_{ik}, x_{ik'}) + f_{spat}(s_i) + \mathrm{b_i} \quad (6)$$

Where μ_i is the mean desired number of children, v_i are covariates assumed to have fixed effects, namely; *sibings, urban, edu1, edu2, male, wealth, working, working2, religion, polygamy;* x_{ij} are continuous covariates assumed to have non-linear effects, namely; *motherAge, ageBirth, marriageBirth;* s_i = (1,2,…,37) is the state of residence for the *ith* respondent, and b_i is the the individual or unit-specific effects. The function f_j are non-linear smooth functions of the continuous covariates, g_k estimates interaction effect of *motherAge*ageBirth*, and *fspat* is the vector of spatial effects. (See the full forms of the coded variables in Table 1).

After model selection, the subsequent inference was Bayesian: For the non-linear effects parameters, we assumed a second-order P-splines; diffuse priors were assumed for the fixed effects parameters, and a Gaussian Markov random field prior was assumed for the spatial effects parameters. For the variance parameters, we utilized standard choices of a=b=0.001; however, as a form of sensitivity analysis, random alternatives of a and b values were also examined for a significant change in results.[18] We carried out 12000 MCMC iterations while thinning out the Markov chain at every 10th iteration, which leads to a random sample of size 1200 for every parameter.

The data were analysed using the R2BayesX package (version 0.3-1) of the R statistical software.[19]

RESULTS

We present the results based on the data analysis earlier described. Descriptive statistics of the dependent variable, the ideal family size for married women, shows that the mean equals 6.5 (range 0-30) and variance equal to 9.91. The histogram of the dependent variable, as shown in Figure 2, shows that the values are non-negative and moderately skewed, which are typical of a count data, and are usually assumed to follow a Poisson distribution. Results from the stepwise regression procedure final model, which was achieved with an AICc value of -315248, produced a more parsimonious model than the full model. For instance, *urban, working2, marriagebirth, age*agebirth interaction,* and the individual or unit-specific effects (See the complete forms of the coded variables in Table 1) were excluded from the model. Further, the respondent's age at first birth which was initially specified as non-linear was estimated linearly.

Findings are discussed based on the fixed effects, nonlinear effects, interaction effects of continuous covariates, and spatial effects. For the mappings, spatial effects are regarded as significant if the 95% credible interval of the MCMC sample does not contain zero.

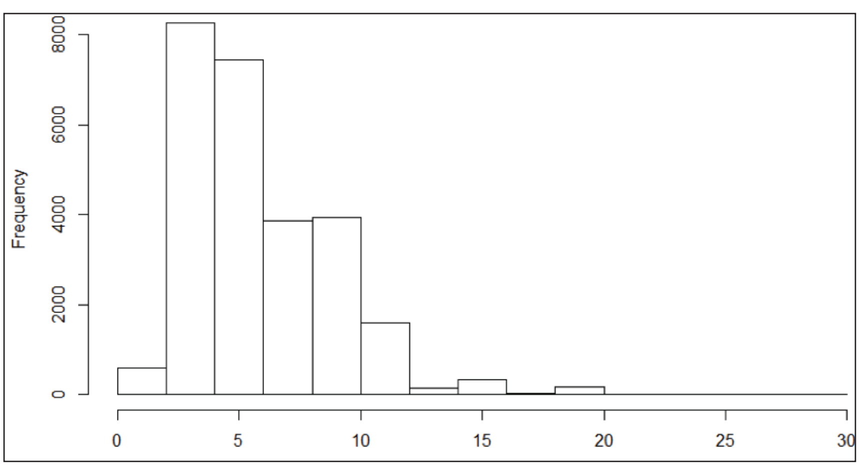

FIGURE 2: Histogram of ideal family size, based on the NDHS 2013 data.

FIXED EFFECTS

The estimates of the posterior mean of the fixed effects and their corresponding credible intervals can be found in Table 2. Findings indicated that the number of siblings the respondent have was significantly related to their family size preference, with a higher number of siblings increasing the desire for more children. Respondent's level of education was significantly associated with the ideal family size, with respondents having primary schooling, secondary or higher education, preferring a smaller family size, compared to those without any formal education. The effects increased in magnitude as the level of education moved from primary to higher education, as observed from the coefficients. Though not significant, the same pattern was found for the respondent's husband's level of education.

The respondent's wealth index was significantly related to the ideal family size: women with a higher wealth index, relative to being poor, desired bigger family size. Women who head their households wanted fewer children than those led by their husbands. On the working status of the women, the results show that working women are associated with a bigger ideal family size than those who are not working.

TABLE 2: Fixed effects estimates of posterior means with 95% credible interval.

			95% Credible Intervals	
Predictor	**Posterior mean**	**Standard Deviation**	**Lower**	**Upper**
Constant	1.5170	0.0335	1.4485	1.5806
Respondent's level of education				
No education (ref)	0			
Primary	-0.0213	0.0081	-0.0365	-0.0048
Secondary	-0.1041	0.0090	-0.1234	-0.0866
Higher	-0.1826	0.0141	-0.2095	-0.1548
Husband's level of education				
No education (ref)	0			
Primary	-0.0134	0.0074	-0.0274	0.0011
Secondary	-0.0065	0.0083	-0.0230	0.0093
Higher	0.0076	0.0108	-0.0133	0.0294
Religion				
None/Traditional(ref)	0			
Christianity	-0.0874	0.0207	-0.1257	-0.0435
Islam	0.0482	0.0202	0.0118	0.0881
Type of marital union				
Monogamy (ref)	0			
Polygamy	-0.0094	0.0053	-0.0197	0.0008
Sex of household head				
Female(ref)	0			
Male	0.0457	0.0076	0.0308	0.0610
Wealth index				
Poor (ref)	0			
Average	-0.0578	0.0067	-0.0710	-0.0435
Rich	-0.1402	0.0105	-0.1610	-0.1204
Number of siblings of respondent	0.0066	0.0009	0.0047	0.0084
Respondent's age	0.0079	0.0003	0.0073	0.0085
Respondent's working status				
Not working (ref)	0			
Working	0.0304	0.0053	0.0202	0.0409

Note: ref denotes the reference category.

Though not significant, women who are in a polygamous marital union desired a fewer number of children than their monogamy counterpart. The age of the women had a positive linear relationship with the ideal family size, with the fertility preference increasing as their number of years of age increased. Relative to women who practised a traditional religion or had no faith, women who practised Islam desired bigger family size; while those who practised Christianity preferred smaller family size.

NON-LINEAR EFFECTS

The result of the non-linear effects of the respondent's age at first birth is shown in Figure 3. Respondents who gave birth to their first child at an early age wanted more children, with a declining trend observed from the ages of 12-18, and a slight increase from the period of 18-22 years; however, a sharp increase was noticed between the ages of 23 and 30 years.

SPATIAL EFFECTS

Figures 4 and 5 show the results of spatial effects in the fitted model. Figure 4 shows the posterior estimates of each of the states. In Figure 5, the states shaded in red colour have a significantly higher posterior estimate, while those blue colour have significantly lower posterior estimates. The grey-shaded states do not have significant spatial effects. There is an interesting North-South spatial pattern: Respondents in the majority of the northeastern states like Borno, Yobe, Bauchi, Gombe, Adamawa, as well as all the northeastern states, are significantly associated with bigger preferred family size. All the southwestern and north-central states, as well as some states, like Rivers, Akwa Ibom, Imo, Abia, Cross River are significantly associated with preference for bigger family size. Bayelsa, Ebonyi and Enugu are the only southern states that are significantly associated with bigger preferred family size. However, this spatial pattern is not significant for some states, like Taraba, Benue, and Anambra.

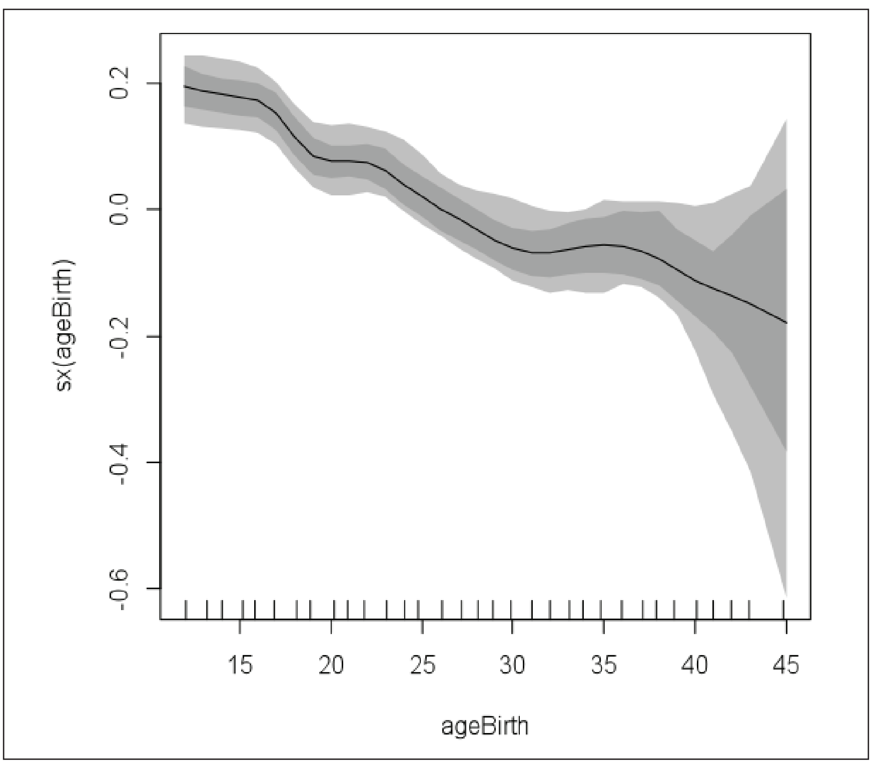

FIGURE 3: Non-linear effect of mother's age at first birth with their corresponding 95% credible intervals.

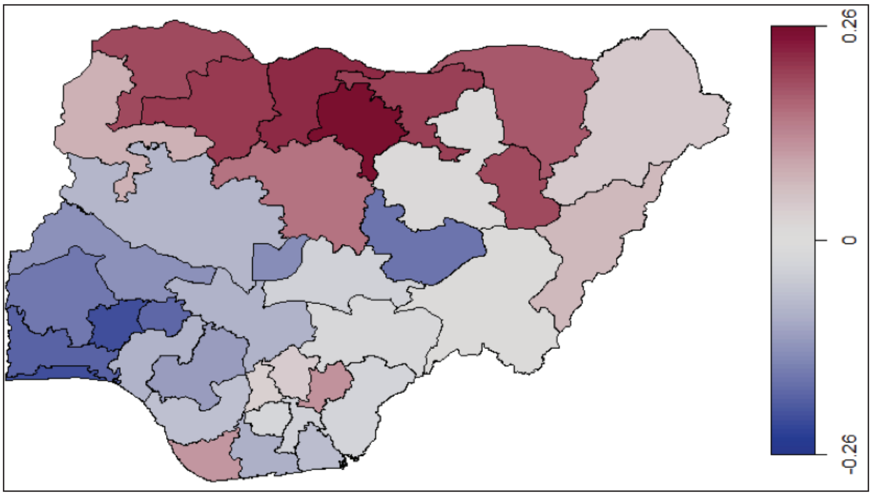

FIGURE 4: Map of Nigeria showing the spatial effects in terms of the posterior mean.

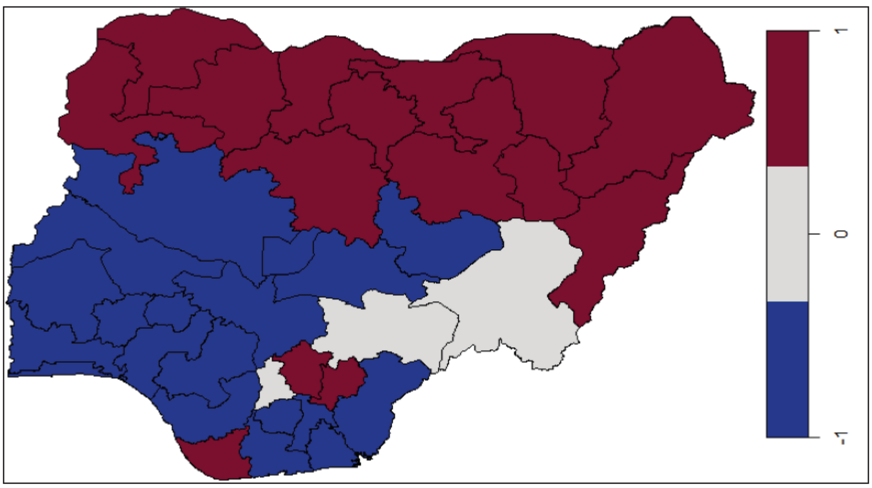

FIGURE 5: Map of Nigeria showing the significance of the spatial effects using its 95% credible interval.

DISCUSSION

In this study, we utilized a geo-additive model, using the Bayesian stepwise regression approach, to investigate the determinants and spatial patterns of the ideal or preferred family size of married women in Nigeria. Rather than relying only on theory to dictate the variables to be included in the model, the stepwise regression approach permits automatic screening of variables to be included in the model and also specifies the form that a continuous covariate enters the model (whether linearly or nonlinearly).

Similar to findings from related studies, our study found that higher educational attainment reduces the preferred family size of women in Nigeria.[3-6] Therefore, an effective intervention that will encourage women's education should be designed for Nigeria to achieve the planned reduction of 0.6 children every five years. As expected, because Islam does not promote conservatism and monogamy, our study agrees with previous related studies that found evidence of a higher number of preferred children for Muslim women.[20] Similar to, we found that women with a relatively higher wealth index preferred smaller family size.[21] Further, contrary to expectation, we found that working women wanted more children than those who do not work. Kazembe had similar findings.[4] Further investigation may be required as to the other factors that explain the high fertility preference among married working women, as done in.[22]

The assumption of linear dependence is often too rigid in many complex real-life applications: The classical parametric regression models for analysing count data have severe problems with estimating small area effects, like state of residence as we have in this study, and simultaneously adjusting for other covariates, particularly when some covariates have non-linear or time-varying effects. For example, modelling mother's age at first birth linearly, in this study, would have insufficiently captured the actual impact in the model. Further, an unusually high number of parameters will be needed for the modelling purposes, which may result in unstable estimates with high variance. Therefore, the adoption of the flexible geo-additive model in this study is justified, as it allows us to incorporate small area spatial effects, non-linear or time-varying effects of covariates and common linear effects in a joint model.

This study adequately provides information on the spatial pattern of married women's preferred family size at the state level, which serves as uniqueness and strength of the adopted model. However, as with most cross-sectional surveys, this study cannot make a causal inference. Another limitation of this study is that the available NDHS data that was utilized is not recent. Consequently, we plan to extend our analyses to the next available NDHS data in future studies.

CONCLUSION

This study complements the existing body of knowledge on fertility-related studies by investigating the determinants and spatial patterns of ideal family size in Nigeria. Particularly interesting is the regional divide we found in the pattern of the preferred family size for the 37 states of the country. Modelling fertility preferences may assist in designing effective interventions leading to an improved child and maternal well-being and economic growth. Family size is directly or indirectly linked with four of the seven components of the Millennium Development Goals (MDGs), which are (i) eradicating extreme poverty, (ii) achieve universal education, (iii) reduce child mortality, and (iii) improve maternal health. Therefore, if findings from this study are used judiciously, government and policymakers will be able to design better strategies that will enable the attainment of these goals.

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Source of Finance

During this study, no financial or spiritual support was received neither from any pharmaceutical company that has a direct connection with the research subject, nor from a company that provides or produces medical instruments and materials which may negatively affect the evaluation process of this study.

Conflict of Interest

No conflicts of interest between the authors and / or family members of the scientific and medical committee members or members of the potential conflicts of interest, counseling, expertise, working conditions, share holding and similar situations in any firm.

Authorship Contributions

Idea/Concept: *Lateef Amusa;* ***Design:*** *Lateef Amusa;* ***Control/Supervision:*** *Waheed Yahya;* ***Data Collection and/or Processing:*** *Lateef Amusa;* ***Analysis and/or Interpretation:*** *Lateef Amusa, Waheed Yahya;* ***Literature Review:*** *Lateef Amusa;* ***Writing The Article:*** *Lateef Amusa;* ***Critical Review:*** *Waheed Yahya*

REFERENCES

1. Heiland F, Prskawetz A, Sanderson WC. Are individuals' desired family sizes stable? Evidence from West German panel data. European Journal of Population/Revue européenne de Démographie. 2008;24(2):129. [Crossref]
2. Baschieri A, Hinde A. The proximate determinants of fertility and birth intervals in Egypt: An application of calendar data. Demogr Res. 2007;16(3):59-96. [Crossref]
3. Bhargava A. Desired family size, family planning and fertility in Ethiopia. J Biosoc Sci. 2007;39(3):367-81. [Crossref] [PubMed]
4. Kazembe LN. Modelling individual fertility levels in Malawian women: a spatial semiparametric regression model. Statistical Methods and Applications (SMA). 2009;18(2):237-55. [Crossref]
5. Alaba OO, Olaomi JO. Geo-additive modelling of family size in Nigeria. J Biom Biostat. 2015;6(3):1-6. [Crossref]
6. Alaba OO, Olubusoye OE, Olaomi J. Spatial patterns and determinants of fertility levels among women of childbearing age in Nigeria. South African Family Practice (SAFP). 2017;59(4):143-7. [Crossref]
7. Makinwa-Adebusoye P, Ebigbola J. Socio-cultural factors affecting fertility and family planning in Nigeria. Federal Republic of Nigeria: Implementing the National Policy on Population Sectoral Report.
8. NDHS. Nigeria Demographic Health Survey. Published by National Population Commission. 2013.
9. Kandala NB, Ghilagaber G. Advanced Techniques for Modelling Maternal and Child Health in Africa. 1st ed. Dordrecht: Springer; 2014. p.330. [Crossref] [PubMed] [PMC]
10. Belitz C, Lang S. Simultaneous selection of variables and smoothing parameters in structured additive regression models. Computational Statistics & Data Analysis (CSDA). 2008;53(1):61-81. [Crossref]
11. Amusa LB. Reducing bias in observational studies: an empirical comparison of propensity score matching methods. Turkiye Klinikleri J Biostat. 2018;10(1):13-26. [Crossref]
12. Fahrmeir L, Kneib T, Lang S, Marx B. Regression: Models, Methods and Applications. 1st ed. Berlin; New York: Springer Science & Business Media; 2013. p.698. [Crossref]
13. Kneib T, Fahrmeir L. Structured additive regression for categorical space–time data: A mixed model approach. Biometrics. 2006;62(1):109-18. [Crossref] [PubMed]
14. Hastie T, Tibshirani R. Generalized additive models for medical research. Stat Methods Med Res. 1995;4(3):187-96. [Crossref] [PubMed]
15. Lang S, Brezger A. Bayesian P-splines. J Comput Graph Stat. 2004;13(1):183-212. [Crossref]
16. Brezger A, Lang S. Generalized structured additive regression based on Bayesian P-splines. Computational Statistics & Data Analysis (CSDA). 2006;50(4):967-91. [Crossref]
17. Besag J, York J, Mollié A. Bayesian image restoration, with two applications in spatial statistics. A Ann Inst Statist Math. 1991;43(1):1-20. [Crossref]
18. Spiegelhalter DJ, Thomas A, Best NG, Gilks W, Lunn D. BUGS: Bayesian inference using Gibbs sampling. Version 05,(version ii) http://www mrc-bsu cam ac uk/bugs. 1996;19.
19. Umlauf N, Kneib T, Lang S, Zeileis A. R2BayesX: Estimate Structured Additive Regression Models with BayesX, 2013. URL http://CRAN R-project org/ package= R2BayesX R package version 03-1.
20. Mazrui AA. Islamic doctrine and the politics of induced fertility change: an African perspective. Popul Dev Rev. 1994;20:121-34. [Crossref]
21. Skirbekk V. Fertility trends by social status. Demogr Res. 2008;18(5):145-80. [Crossref]
22. Kravdal O. A search for aggregate-level effects of education on fertility, using data from Zimbabwe. Demogr Res. 2000;3:[35]. [Crossref] [PubMed]