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Research Article

A Bayesian semiparametric multilevel survival modelling of age at first birth in Nigeria

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Abstract

BACKGROUND
The age at which childbearing begins influences the total number of children a woman bears throughout her reproductive period, in the absence of any active fertility control. For countries in sub-Saharan Africa where contraceptive prevalence rate is still low, younger ages at first birth tend to increase the number of children a woman will have thereby hindering the process of fertility decline. Research has also shown that early childbearing can endanger the health of the mother and her offspring, which can in turn lead to high child and maternal mortality.

OBJECTIVES
In this paper, an attempt was made to explore possible trends, geographical variation and determinants of timing of first birth in Nigeria, using the 1999 – 2008 Nigeria Demographic and Health Survey data sets.

METHODS
A structured additive survival model for continuous time data, an approach that simultaneously estimates the nonlinear effect of metrical covariates, fixed effects, spatial effects and smoothing parameters within a Bayesian context in one step is employed for all estimations. All analyses were carried out using BayesX – a software package for Bayesian modelling techniques.

RESULTS
Results from this paper reveal that variation in age at first birth in Nigeria is determined more by individual household than by community, and that substantial geographical variations in timing of first birth also exist.

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COMMENTS
These findings can guide policymakers in identifying states or districts that are associated with significant risk of early childbirth, which can in turn be used in designing effective strategies and in decision making. These findings can also point in the direction of effective utilisation of scarce resources: a major challenge to those effecting interventions in developing countries.

1. Introduction

Early life events have a strong tendency to influence later ones. The timing of first birth is known to impact both demographic and non-demographic phenomena in the life course of women (Taniguchi 1999, Mirowsky and Ross 2002). In sub-Saharan Africa, the timing of first birth has strong effects on both individual and aggregate levels of fertility, as well as broader implications for women's roles and social changes in general. In the absence of any effective contraceptive, or where contraception is only being used for spacing, but not for limiting, fertility, the total number of children a woman bears is principally a function of the age at which childbearing begins (Gyimah 2003). This is, however, not always the case in developed countries, where the pervasiveness of low fertility norms and increasing use of modern contraceptives mean that young women who gave birth early in life avoid childbearing later (Grindstaff, Balakrishnan, and Dewit 1991). Early childbearing can interrupt a young woman's education and also limit her opportunity in modern economy. Women who begin childbearing early in life spend less time preparing for their careers, limiting them to low social economic status and ultimately reinforcing fertility. Early childbearing also endangers the health of the mother and her offspring and contributes to high child and maternal mortality. It also exposes young women to a high risk of HIV infection, due to lack of bargaining power with their partners (generally older and often HIV positive) in regard to the use of condoms.

The decline in fertility in most societies often proceeds in two stages. The first stage is the decline in fertility due to an increase of age at first birth (natural fertility control) (Gupta and Mahy 2003). This stage is more applicable in developing countries where timing of first birth is known to affect completed fertility. Early childbearing, high infant mortality, low education and contraceptive use, and persistence of high fertility-sustaining societal values and norms have been identified as prominent factors causing African women to have more children than their counterparts in other parts of the world (Caldwell and Caldwell 1987, Takyi and Addai 2002, Gyimah 2003). In developed countries, especially Canada and the United States, it has, however, been established that the strength of association between the inverse relationship of timing of first birth and fertility has weakened over time (Balakrishnan et al. 1988, Wineberg 1988, Grindstaff, Balakrishnan, and Dewit 1991). Timing of first birth is no longer a significant determinant of completed fertility in these places.

The second stage involves the adoption of contraception and a change in fertility behaviour (Ngalinda 1998). Population policies and corresponding strategies for implementing such policies in Nigeria have focused on lowering fertility rates by encouraging family planning. The first stage of fertility transition, age at first birth, has received little attention, however.

Researchers have shown much interest in proximate determinants of fertility in sub-Saharan Africa (Makinde-Adebusoye and Ebigbola 1992, Foote, Hill, and Martin 1993, Cleland, Onuoha, and Timaeus 1994, Cohen 1998, Makinde-Adebusoye 2001, Caldwell and Caldwell 2002, Norville, Gomez, and Brown 2003, Baschieri and Hinde 2007, Kazembe 2009). One major reason is that, by the standards of the rest of the world, fertility levels in African countries are still high (Caldwell and Caldwell, 2002). This continued high fertility means that the number of people in need of health, education, and economic empowerment and other services has been on the increase. The result is developmental problems related to economic growth and poverty, as well as maternal and child health (Shen and Willianson 1999, Birdsall, Kelley, and Sinding 2003, Adebayo et al. 2013). The majority of these researchers concentrate on other determinants of fertility but ignore the timing of first birth. Their argument is that childbearing only occurs within marriage. This might be true for populations where there are strong proscriptions of female premarital sexual activity and a great majority of brides are virgins. African sexual patterns are very different from this. It is characterized by widespread premarital sexual relation for both males and females (Caldwell, Orubuloye, and Caldwell 1992, Gayawan et al. 2010). In a study in Ekiti, Southwest Nigeria, Orubuloye, Caldwell and Caldwell (1991) found that four-fifths of urban women and two-thirds of rural women were not virgins at marriage. This scenario is not likely to have been different if this study had been extended to other parts of the country. This pattern, coupled with low rates of contraception in Nigeria, contribute to a continuing high rate of birth outside of marriage. It is desirable to consider age at first birth as a fertility determinant. The analysis of age at first birth among women in Nigeria is the aim of this article.

Usually, the timing of first birth is measured in years and assumed to be continuous (Zhang and Steele 2004, Kazembe 2009). This is often modelled using the classical parametric regression analysis. Parametric regression models for analysing these sets of data have severe problems when estimating small area effects and simultaneously adjusting for other covariates, in particular, when the effects of the covariates are nonlinear or time-varying. In such a case, high numbers of parameters would be required, and this might result in an unstable estimate with high standard errors (Adebayo 2004). Therefore, flexible semi-parametric models that jointly model spatial effects, nonlinear or time-varying effects of covariates, as well as linear fixed effects, are required.

In demographic studies, event histories are usually modelled using Cox proportional hazard function (Santow and Bracher 1994, Baschieri and Hinde 2007). This function assumes that time is measured on a continuous scale and is based on proportional hazard assumption. Event histories are obtained in demographic surveys of women in which information is given in retrospect, making it subject to error. Older or less educated respondents, for instance, are less likely to recall with accuracy the actual dates of events, or facts such as age at first giving birth. As a result, events that occurred at different periods could be reported as having occurred at the same time resulting in large numbers of tied survival times. Estimation of the model with such heavily tied survival times would generally result in inconsistent estimators (Prentice and Gloeckler 1978). Breaking ties by slight adjustment introduces accuracy bias into the data. Another approach which has been adopted to study age at first marriage by Manda and Meyer (2005), childhood mortality by Adebayo and Fahrmeir (2005) and Kandala and Gebrenegus (2006) among others, is to use such event history data as discrete-time analysis, but this approach has also been found to result in loss of information (Kneib 2006). A possible way out of this problem is to assume that an event occurs over an interval of time (Kneib 2006). Within the interval-censoring framework, the heavily tied survival times are incorporated by introducing larger intervals for the heaped observations.

The data analyzed in this study are from the Nigerian Demographic and Health Survey (NDHS). This survey follows a two-stage cluster sampling, in which clusters were selected at the first stage and eligible women were selected at the second stage. Observations from the same clusters are very likely to be correlated due to unobserved community factors. These might include traditional norms, access to family planning, and reproductive health programmes, which may influence the timing of first giving birth in a given community, but may vary between communities. Further, in some cases, as in Nigeria, populations in adjacent areas are likely to display similar behavior, which can influence timing of first birth and causing it to be spatially auto-correlated. Failure to take into account clustering in analysing data from such hierarchical populations typically leads to underestimation of standard errors (Goldstein, 2003). A modelling technique that accounts for correlation within clusters is therefore required. In this study, we use a structured geo-additive hazard regression model for continuous time survival data that permits modelling of linear and nonlinear covariate effects, unobserved covariates (log-frailties,) as well as spatial effects, in a semi-parametric Bayesian approach (Hennerfeind, Brezger, and Fahrmeir 2006, Kneib and Fahrmeir

2007). In addition, this approach allows flexible nonparametric modelling of the (log-) baseline hazard rate, as it is expected that the hazard will change smoothly between time points. Hidden patterns such as peaks and bumps may be established, which would not have been possible within parametric models.

A number of studies that have been carried out using survey data in Nigeria have reported significant random effect at community and family levels (Uthman 2008, Uthman and Kongnyuy 2008, Agho et al. 2011). Others have investigated the role of spatially distributed factors. Adebayo (2004) studied spatial variations in breastfeeding initiation in Nigeria; Kandala, Nwakeze, and Kandala (2009) studied the spatial distribution of female genital mutilation in Nigeria; Uthman (2008) looked at the geographical variation and contextual effects on age of initiation of sexual intercourse among Nigerian women; Adebayo et al. (2011), considered possible geographical variations in multiple sexual partnering in Nigeria. However, to the best of our knowledge, studies on spatial patterns of timing of first birth in Nigeria have not been undertaken. Taking advantage of the available geo-referenced data in the NDHS, this study acknowledges the hierarchical nature of the NDHS data set, and simultaneously models for any spatial variation in the data.

The data used in this study are described in Section 2. We describe the methodology for data analysis in Section 3, while results are presented and discussed in Sections 4 and 5, respectively.

2. Data

This study is based on data from the 1999, 2003 and 2008 NDHS. The Demographic and Health Survey (DHS) is conducted in many developing countries by Measure DHS (www.measuredhs.com) to provide cross-sectional information on demographic and health indicators, including information on fertility and family planning, knowledge and current use of contraception methods, as well as sexually transmitted diseases. The survey is designed to provide this information at national, regional, and state or district levels, for both urban and rural areas. The standard methodology with which the surveys are being carried out permits comparisons of indicators across years, and across all countries where it is conducted. The data sets utilized in this paper allows us to study trends in timing of first birth in Nigeria between 1999 and 2008.

The sampling frame used for the surveys was based on the Population and Housing Census of the Federal Republic of Nigeria conducted in 1991 and 2006. The primary sampling unit (PSU,) referred to as “cluster” for the survey, was defined on the basis of enumeration areas (EAs) from the census frames. The NDHS sample was selected using a two-stage stratified design. At the first stage, a number of clusters were selected from the list of enumeration areas, while households to participate in the survey were selected at the second stage. One of the eligibility criteria for the female component of the survey is that respondents must be in the age range 15-49 years. The 2008 survey was a significant improvement on the 1999 and 2003 surveys in scope and content. Whereas 34,070 households were selected and successfully interviewed in the 2008 survey, 7,225 households in 2003 and 7,647 households in 1999 were selected and interviewed. Of these, the response rates for the eligible women in the households were 92%, 95% and 97%, for the 1999, 2003 and 2008 surveys respectively.

As in previous studies, relevant determinants that were known to be associated with timing of first birth at the individual and community levels were included in this study (Addai 1999, Gupta and Mahy 2003, Gyimah 2003). At the individual level, we considered the following explanatory variables: respondent's age, age at first sexual intercourse, age difference between the woman respondent and her head of household (age gap), woman's highest educational attainment, religion, ethnicity, contraceptive use (before the birth of the first child), working status, type of marital union, and sex of household head. Age at first sexual intercourse is included, as childbearing cannot take place unless one engages in sexual activities that eventually lead to pregnancy. The conventional marker of the beginning of exposure to the risk of pregnancy is the date of first marriage. However, in Nigeria, sexual activity is not confined to marriage and women bear children before the date of first marriage. Age at first sexual intercourse and date of first birth are therefore more appropriate indicators of the beginning of sexual exposure than the date of first marriage in Nigeria. We included age gap to measure the equity between a woman and her partner for those whose partner is the head of their households, and between the woman and her guardian or parent, in the case of those who are single. Women's level of education affects their knowledge and awareness of modern contraceptive methods and usage, and delays entry into marriage, which reduces the exposure time to risk of childbearing. This is also linked to women's working status. Differences in childbearing behaviour have been found to exist between various religious groups (Lucas 1980, Ngalinda 1998). Studies in Ghana have found ethnicity-specific practices, norms and values that affect the risk of birth (Addai 1996, Gyimah 2003). These variables were therefore included in this case study. We use respondent's age to study the effects of generational change on age at first birth in Nigeria. It needs to be stated that women aged 15 years old in the 2008 survey were not, for example, the same as those with this age during the 2003 survey. However, as the samples were randomly drawn from the same population, subject to the attrition of mortality, the merged data set can be used to estimate the parameters of interest (Gyimah 2003). Table 1 presents a description of the variables included in the analyses, including their frequency distributions.

Table 1: Empirical frequencies of variables included in the analyses

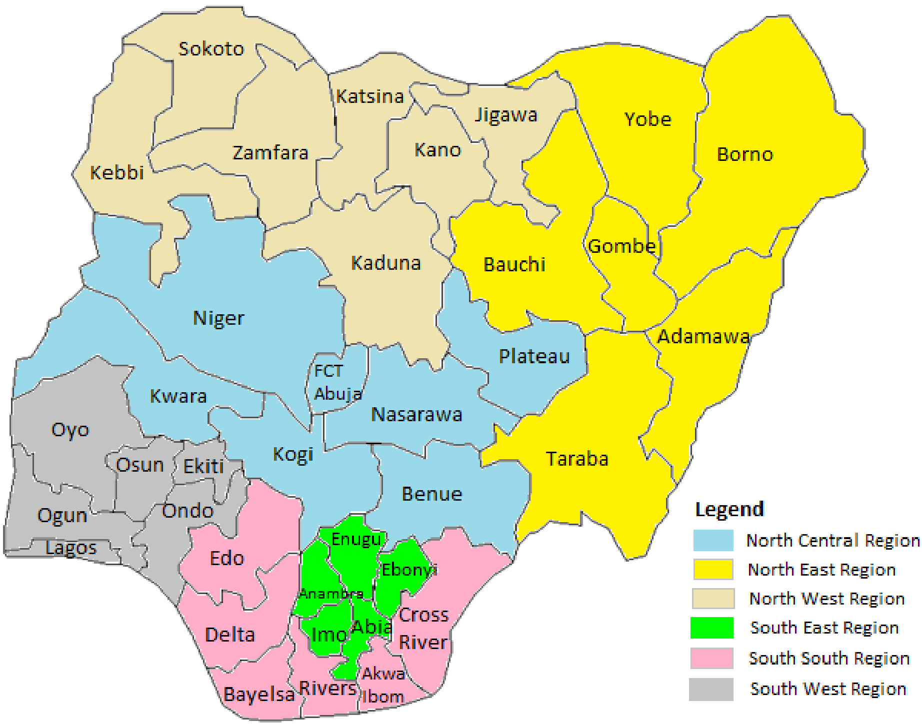
Variable	N	Percentage
Trend		
Year 1999	9810	21.3
Year 2003	7620	16.5
Year 2008	28647	62.2
Region of residence		
North Central	8041	17.5
North East	9222	20.0
North West	12608	27.4
South East	4643	10.1
South West	6231	13.5
South South	5332	11.5
Place of residence		
Rural	32189	69.9
Urban	13888	30.1
Level of education		
No education	21129	45.9
Primary	10910	23.7
Secondary	11691	25.3
Higher	2347	5.1
Religion		
None/Traditional religion	874	1.9
Catholic	5069	11.0
Other Christians	15875	34.5
Islam	24046	52.1
Missing	213	0.5
Ethnicity		
Other	22163	48.1
Hausa	11639	25.3
Igbo	5943	12.9
Yoruba	5996	13.0
Missing	336	0.7

Table 1: (Continued)

Variable	N	Percentage
Contraceptive use		
No	42677	92.6
Yes	3251	7.1
Missing	149	0.3
Working status		
No	19239	41.8
Yes	26572	57.7
Missing	266	0.5
Marital union		
Monogamous	25111	54.5
Polygyny	12839	27.9
Single	7734	16.7
Missing	393	0.9
Sex of household head		
Female	5458	11.8
Male	40619	88.2

At the community level, region (geopolitical zone) and type of place of residence of the respondent given as urban or rural were included. Type of place of residence was included to capture the effects of urbanization and modernization while region of residence was to capture the large-scale socio-economic, geographical and political differences that exist in Nigeria. Nigeria is divided into six regions, altogether comprising 36 states, and the Federal Capital Territory (FCT), Abuja (Figure 1). After controlling for the observed covariates, the unobserved heterogeneity at various levels of the hierarchy using community and family random effects were also explored. The variable used for community random effects is V001: Cluster code, where cluster is a combination of one or more enumeration areas (EA) that demarcate the mapping of locality selected for interview. Traditional norms; common access to family planning and reproductive health programmes; sanctions against premarital childbirth; cultural approval of marriage and practice may jointly account for variations in age at first birth between communities. At the family level, social status and traditional belief which may influence family decisions could also constitute unmeasured explanatory factors that affect decision as to the timing of first birth (Maitra 2004, Manda and Meyer 2005).

Figure 1: Map of Nigeria showing the 36 states and Federal Capital Territory, Abuja



3. Statistical analysis

3.1 Geo-additive hazard model

Let v_i be observed covariates. The standard approach for analyzing the impact of the covariates on the survival times is the Cox proportional hazard model, where the multiplicative structure

$$\lambda_i = \lambda(t, v_i) = \lambda_0(t)\exp(v_i^{'}, \gamma) \tag{1}$$

is assumed for the hazard rate. In equation (1), γ is a vector of regression coefficients and $\lambda_0(t)$ is the baseline hazard rate. In the classical approach, $\lambda_0(t)$ is unspecified, and estimation of the regression coefficients is based on the partial likelihood. This model is, however, based on the proportional hazard assumption. In addition, while allowing for a flexible baseline hazard rate, the Cox model assumes a parametric form for all covariates, which may be too restrictive in realistically complex applications. Moreover, it does not incorporate spatial correlations. Re-parameterizing the baseline hazard rate through $g_0 = \log(\lambda_0(t))$ and partitioning covariates into groups of different types, Hennerfeind, Brezger and Fahrmeir (2006) and Kneib and Fahrmeir (2007) extended the Cox model to a semi-parametric hazard rate model, thus

$$\lambda_i(t) = \exp(\eta_i(t)) \qquad i = 1,2,\ldots,n \tag{2}$$

where $\eta_i(t)$ is a geo-additive predictor of the form

$$\eta_i(t) = v_i'\gamma + g_0(t) + \sum_{j=1}^{J} f_j(x_{ij}) + \sum_{k=1}^{K} f_k(x_{ik}, x_{ik}) + f_{spat}(s_i) + b_{gi} \ . \tag{3}$$

In equation (3), $f_j(x_{ij})$ is the non-linear effect of continuous covariates x_j, $f_k(x_{ik}, x_{lk})$ is an interaction term between two covariates and $f_{spat}(s)$ is the spatial effect. The vector of the linear effects is denoted γ while b_g, $g \in \{1,\ldots,G\}$ are uncorrelated individual or group-specific frailties. In a further step, Kneib (2006) proposed an extended geo-additive Cox model that combines the ability to deal with arbitrary combinations of left, right, and interval censoring schemes. The geo-additive version also relaxes the proportional hazard assumption by allowing all covariates to be (piecewise constant) time varying. See Fahrmeir and Kneib (2011) for further details and other extensions of the model.

The predictor (3) can be expressed in matrix notation. Let $\boldsymbol{\eta} = (\eta_1,\ldots,\eta_i,\ldots,\eta_n)'$ denote the predictor vector, and let $\mathbf{g_l} = (g_l(t_1),\ldots,g_l(t_n))'$ denote the vector of evaluations of functions $g_l(t)$, $\mathbf{f_j} = (f_j(x_{1j}),\ldots,f_j(x_{nj}))'$ the vector of evaluations of the functions $f_j(x_j)$, $\mathbf{f_{spat}} = (f_{spat}(s_1),\ldots,f_{spat}(s_n))'$ the vector of spatial effects and $\mathbf{b} = (b_{g1},\ldots,b_{gn})'$ the vector of uncorrelated random effects. These vectors can be expressed as a matrix product of a design matrix $\boldsymbol{Z}$ and vector of parameters $\boldsymbol{\beta}$, i.e. $\mathbf{g_l^*} = \mathbf{Z_1\beta_1}$, $f_j = \mathbf{Z_j\beta_j}$, etc. After appropriate re-indexing, the predictor vector $\boldsymbol{\eta}$ can be represented in a generic notation as

$$\boldsymbol{\eta} = \mathbf{V}\boldsymbol{\lambda} + \mathbf{Z_1}\boldsymbol{\beta_1} + \ldots + \mathbf{Z_p}\boldsymbol{\beta_p}\,. \tag{5}$$

Under the common assumption of non-informative censoring and conditional independence, the likelihood of $\theta = (\gamma', \beta_1', ..., \beta_p')$ for an interval-censored observation is given by

$$L_i(\theta) = \exp\left(-\int_0^{T_j} \lambda(t)dt\right)\left(1 - \exp\left(-\int_{T_l}^{T_u} \lambda(t)dt\right)\right). \tag{6}$$

3.2 Bayesian prior probability distribution

An entirely Bayesian approach was used to estimate smooth effect functions and model parameters, as developed in Fahrmeir and Lang (2001) and Lang and Brezger (2004). We assigned appropriate priors for all parameters and priors. Diffuse priors were assumed for the fixed effect parameters. For the baseline effect, $g_0(t)$ and nonlinear effects, $f_j(x_{ij})$ Bayesian P-spline[3] prior based on Lang and Brezger (2004) and Brezger and Lang (2006) was assumed. The P-splines prior allows for nonparametric estimation of *f* as a linear combination of basis function (B-splines)

$$p(z) = \sum_{t=1}^{m} \alpha_t B_t(z) \tag{7}$$

where $B_t(z)$ are B-splines and the coefficients α_t are further defined to follow a second order Gaussian random walk smoothness priors

$$\alpha_2 = 2\alpha_{j-1} - \alpha_{j-2} + \varepsilon_1$$

[3] The term P-spline (penalized B-spline) refers to using the B-spline (basis spline) representation where the coefficients are determined partly by the data to be fitted and partly by an additional penalty function that aims to impose smoothness to avoid over-fitting. Bayesian P-spline is achieved by replacing difference penalties by their stochastic analogues i.e. Gaussian (intrinsic) random walk priors, which serve as smoothness priors for the unknown regression coefficients. Further clarification on this can be obtained from Eilers and Marx (1996), Lang and Brezger (2004) and Brezger and Lang (2006).

with *i.i.d*. errors $\varepsilon_t \sim N\left(0,\tau^2\right)$. The variance τ^2 controls the smoothness of *f*. Assigning a weakly informative inverse Gamma prior $\tau^2 \sim IG(\varepsilon,\varepsilon)$, with ε very small, it is estimated jointly with the basis function coefficients.

Random effects $\left(b_{gi}\right)$ were modelled by assuming exchangeable normal priors, $b_{ij} \sim N\left(0,\tau_b^2\right)$, where τ_b^2 is a variance component that incorporates over-dispersion and heterogeneity. For the spatial effects $f_{spat}(s)$, we chose a Gaussian Markov random field prior, which is commonly used in spatial statistics, see Besag, York and Mollie (1991). It is given as

$$\left[f_{spat}(s) \mid f_{spat}(t); t \neq s, \tau^2\right] \sim N\left(\sum_{t \in \partial_s} \frac{f_{spat}(t)}{N_s}, \frac{\tau^2}{N_s}\right)$$

where N_s is the number of adjacent sites and $t \in \partial_s$ denotes that site *t* is a neighbour of site *s*. The prior defines areas as neighbours if they share a common boundary and neighbouring areas are assumed to have similar patterns. The (conditional) mean of $f_{spat}(s)$ is an average of function evaluations $f_{spat}(t)$ of neighbouring sites *t*. Again, τ^2 controls the amount of spatial smoothness.

In order to be able to estimate the smoothing parameters for nonlinear and spatial effects, highly dispersed but proper hyper-priors are assigned to them. Hence, for all variance components, an inverse gamma distribution with hyper-parameters *a* and *b* is chosen, e.g. $\tau^2 \sim IG(a,b)$. Standard choices for the hyper-parameters are a=1 and b=0.005 or a=b=0.001.

Fully Bayesian inference is based on the posterior distribution of the model parameters, which are not of a known form. Therefore, Markov chain Monte Carlo (MCMC) sampling from full conditionals for nonlinear effects, spatial effects, fixed effects, and smoothing parameters is used for posterior analysis. Fitting Bayesian models via MCMC entails treating all parameters as randomly distributed according to some prior distribution. The posterior distribution is intractable, so MCMC algorithms are used to generate samples from this prior distribution, which allows estimation and inference for the parameters. All analyses were carried out in BayesX - a software for Bayesian inference in Structured Additive Regression Models - version 2.0.1 (Belitz et al. 2009). For each of the models considered in this study, 12,000 iterations were carried out with a burn-in period of 2,000. We investigated sensitivity to choice of priors by varying the values of hyper-parameters *a* and *b*. It turned out that the results are stable for $a = b = 0.001$. This is similar to what other authors have experienced (Adebayo and Fahrmeir 2005, Kazembe 2009). Further, a plot of sampling paths shows evidence of convergence. Detailed numerical methods of implementing survival time models are described in the reference manual of BayesX (Belitz et al. 2009).

3.3 Model diagnostics

Model diagnostics were based on the Deviance Information Criterion (DIC) (Spiegelhalter et al. 2002) given by $DIC = \overline{D}(\theta) + pD$, where $\overline{D}$ is the posterior mean of the deviance, measuring how well a model fits the data, and pD is the effective number of parameters measuring model complexity. The DIC is analogous to the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). It is useful in situations involving complex hierarchical models in which it is difficult to compute the actual number of parameters being used, especially when the models contain nonparametric and random effect components. Small values of $\overline{D}(\theta)$ indicate good fit while small values of pD indicate a parsimonious model. The model with the lowest *DIC* is therefore considered as best.

4. Data analysis and results

4.1 Data analysis

In order to understand the influence of both observed covariates and unobserved heterogeneity on timing of first birth in Nigeria, six hazard models of different specifications were fitted. The fitted models are defined as follows:

M_1: $\eta_i = g_0(t) + t_1 + t_2 + f_{spat}(s_i)$

M_2: $\eta_i = g_0(t) + f_{spat}(s_i) + b_{1i} + b_{2i}$

M_3: $\eta_i = g_0(t) + t_1 + t_2 + v_i'\gamma + f_1(age\_sex) + f_2(age) + f_3(age\_gap) + f_4(age * age\_gap) + f_{spat}(s_i)$

M_4: $\eta_i = g_0(t) + t_1 + t_2 + v_i'\gamma + f_1(age\_sex) + f_2(age) + f_3(age\_gap) + f_4(age * age\_gap) + f_{spat}(s_i) + b_{1i}$

M_5: $\eta_i = g_0(t) + t_1 + t_2 + v_i'\gamma + f_1(age\_sex) + f_2(age) + f_3(age\_gap) + f_4(age * age\_gap) + f_{spat}(s_i) + b_{2i}$

M_6: $\eta_i = g_0(t) + t_1 + t_2 + v_i'\gamma + f_1(age\_sex) + f_2(age) + f_3(age\_gap) + f_4(age * age\_gap) + f_{spat}(s_i) + b_{1i} + b_{2i}$

In these models, $g_0(t)$ is the baseline hazard function; t_1 and t_2 are the dummy variables for second and third rounds of the surveys (i.e. 2003 and 2008) respectively setting 1999 as the reference category; v_i' is the vector of fixed effect factors; and *f(age), f(age_sex), f(age_gap)* and *f(age*age_gap)* are smooth functions of age, age at first sexual intercourse, age gap, and the interaction effect of age and age gap, respectively. The household and community random effects are b_{1i} and b_2 , respectively. In model M_1, we modelled the dependence of age at first birth on year of study and spatial effect. Our goal was to assess any possible trend or geographic aspect affecting timing of first birth in Nigeria, without taking any variables into account. Model M_2 examines the effects of unobserved community and household random effects and possible geographical variations due to these unobserved heterogeneities on age at first birth. All covariates described in Section 2 were included in model M_3 without adjusting for any random effect. This model was used to assess the gains of fitting a model with random effects. In addition to all covariates, household random effects were included in model M_4 while community random effects were controlled for in model M_5. With these, we could assess the residual variation at the household and community levels. Finally, in model M_6, we controlled for both community and household random effects in addition to all covariates in model M_3. Table 2 summarises the structure of nesting for the models.

Table 2: Nesting structure of models M_1 to M_6

Model	Baseline $(g_0(t))$	Time (t_1 & t_2)	Fixed effect (v_j')	Nonlinear effect	Random effect		Spatial effect (s_i)
					Household (b_{1i})	Community (b_{2i})	
M_1	√	√					√
M_2	√				√	√	√
M_3	√	√	√	√			√
M_4	√	√	√	√	√		√
M_5	√	√	√	√		√	√
M_6	√	√	√	√	√	√	√

4.2 Results

Before proceeding to elaborate analyses, Table 3 presents a tabulation of the mean and percentage distribution of all children ever born by age at first birth for 2008 survey. It is evident from the Table that there exists an inverse relationship between age at first birth and completed fertility in Nigeria. For every unit increase in age at first birth, the percentage of women who give birth to 7 or more children is reduced. While, for instance, about 31% of women who had their first child before age 15 years ended up having 7 or more children, only 8.3% of those who had first birth after age 25 years ended with this number. The corresponding mean numbers of children for these women are 6.62 and 2.62 respectively, a difference of 4.0. Table 4 presents model diagnostics statistics for all the fitted models. It is clear from the Table that model M_5 that incorporates community random effects in addition to all other covariates performed best when compared with all other models. Comparing models M_4 and M_6 shows that model M_4 was relatively better than M_6 simply because inclusion of community random effect in M_6 increased model complexity (pD = 771.638), which offset the gains made in the goodness of fit. Discussions of results will be based on models $M_{1,}$ M_2 and M_5 only. Model M_1 was selected for discussion because it was meant to examine geographical variation in crude age at first birth without taking into account any variable except year of study. Model M_2 was selected because the effects of unobserved community and household random effects and possible geographical variations due to these unobserved heterogeneities on timing of first birth were examined. Model M_5 was chosen because it provides the best fit.

Table 3: Percentage distribution and mean of children ever born (CEB) by age at first birth

Age at first birth	Children ever born 1	2	3	4	5	6	≥ 7	Total %	Mean CEB	Sample size
< 15	2.5	8.5	13.3	14.5	14.0	11.8	35.4	100	6.62	2708
15	5.4	13.0	13.8	13.1	13.3	10.7	30.7	100	5.23	2710
16	9.0	16.4	14.7	13.5	12.3	8.7	25.4	100	4.74	3030
17	11.1	17.2	13.3	14.4	11.3	10.7	22.0	100	4.56	3275
18	11.2	14.0	18.5	15.3	12.0	9.9	19.1	100	4.36	2940
19	12.5	14.7	20.0	14.7	11.3	8.0	18.8	100	4.26	2569
20	11.3	17.5	17.3	14.1	12.5	8.4	18.9	100	4.24	2287
21	10.5	21.2	19.1	14.8	10.5	8.5	15.4	100	4.00	2056
22	11.6	22.6	18.0	15.0	10.3	7.5	15.0	100	3.98	1564
23	14.6	20.4	17.8	12.3	11.9	8.8	14.2	100	3.86	1239
24	14.9	20.7	20.2	13.3	10.5	7.4	13.0	100	3.78	1071
25	14.2	22.7	21.2	12.1	9.5	8.1	12.2	100	3.70	854
> 25	18.9	25.9	18.6	14.8	8.5	5.0	8.3	100	2.62	2344

Table 4: Model diagnostic statistics

Model	$\overline{D}$	*pD*	DIC
M_1	224615.00	51.323	224717.65
M_2	221829.10	960.807	223750.71
M_3	195097.39	97.890	195293.17
M_4	191134.52	177.095	191488.71
M_5	189147.31	748.194	190643.70
M_6	189966.92	771.638	191510.20

4.2.1 Trend and fixed effects

Table 5 presents results of fixed effects of models M_1 and M_5. Presented are the posterior means, standard deviations, and 95% credible intervals. Results indicate similar pattern of trend for the two models. Compared to 1999, findings reveal that there is evidence of reduction in the relative risk of bearing first child in 2003. However, compared to 1999, the risk increased substantially in 2008. Findings indicate substantial regional differentials in risk of first giving birth in Nigeria. Compared to women from the North Central region, results show evidence of higher risk for those in the North East region, while an insignificantly lower risk is observed for the other regions. An insignificantly higher risk of bearing the first child was also observed for women who reside in urban areas, compared to their counterparts in rural areas.

Table 5: Estimates of posterior means of the fixed effect parameters for models M_1 and M_5

Parameter	Results for model M_1				Results for model M_5			
	Mean	SD[1]	95% Credible Interval[2]		Mean	SD	95% Credible Interval	
			Lower	Upper			Lower	Upper
Constant	-10.618	1.474	-13.648	-7.977	-9.244	1.103	-11.341	-7.329
Trend								
Year 1999 (ref)	0.0				0.0			
Year 2003	-0.111	0.009	-0.131	-0.093	-0.119	0.013	-0.147	-0.093
Year 2008	0.250	0.008	0.235	0.266	0.193	0.011	0.170	0.214
Region of residence								
North Central (ref)					0.0			
North East					0.143	0.060	0.023	0.265
North West					-0.020	0.068	-0.149	0.117
South East					-0.046	0.072	-0.168	0.110
South West					-0.050	0.044	-0.132	0.033
South South					-0.070	0.046	-0.160	0.016
Place of residence								
Rural (ref)					0.0			
Urban					0.012	0.009	-0.005	0.032
Level of education								
No education (ref)					0.0			
Primary					0.195	0.011	0.174	0.217
Secondary					-0.070	0.012	-0.092	-0.047
Higher					-0.279	0.019	-0.321	-0.246
Religion								
None/Traditional religion (ref)					0.0			
Catholic					0.013	0.020	-0.027	0.049
Other Christians					-0.015	0.015	-0.043	0.016
Islam					-0.011	0.017	-0.046	0.022
Ethnicity								
Other ethnicity (ref)					0.0			
Hausa					0.021	0.020	-0.019	0.058
Igbo					-0.099	0.027	-0.157	-0.042
Yoruba					0.025	0.023	-0.013	0.075
Contraceptive use								
No (ref)					0.0			
Yes					-0.219	0.012	-0.241	-0.195

Table 5: (Continued)

Parameter	Results for model M_1				Results for model M_5			
	Mean	SD[1]	95% Credible Interval[2]		Mean	SD	95% Credible Interval	
			Lower	Upper			Lower	Upper
Working status								
No (ref)					0.0			
Yes					0.074	0.006	0.062	0.086
Marital union								
Monogamous (ref)					0.0			
Polygyny					0.410	0.016	0.380	0.447
Single					-0.858	0.028	-0.909	-0.801
Sex of household								
head					0.0			
Female (ref)					-0.085	0.011	-0.105	-0.060
Male								

[1] Standard deviation

[2] Bayesian credible intervals are different from frequentist confidence intervals in some ways, including (i) their interpretations, with a given probability that the true parameter lies in a related credible interval, unlike in the frequentist approach where this probability for any interval can be only 0 or 1; and (ii) incorporation of problem-specific contextual information from the prior distribution making the credible intervals generally narrower, as opposed to confidence intervals being based only on the data (Spiegelhalter, Abrams, and Myles 2004).

Education was found to be positively associated with timing of first birth. The risk of bearing the first child is lower for women who attend secondary and higher education than those who have no education. However, our results show that women that had only primary education at the period of the surveys possess a substantially higher risk of bearing their first child than did those who have no education. Compared to women who practise traditional religion or who practice no religion, an insignificantly lower risk of bearing a first child occurred for those in the Islamic and other Christian religions, whereas an insignificantly higher risk occurred for Catholic women. While the results provide evidence that the Igbo women are associated with lower risk, there is no evidence that the risks for the Hausa and Yoruba women, though higher, are substantially different from that of women in other ethnic groups. As expected, use of contraceptive methods before the birth of the first child leads to a substantial reduction in risk of bearing a first child, compared to those women who did not use any contraceptive. The working status of the women does not indicate any substantial reduction in risk of giving birth to the first child. In fact, the results show that a working woman has a higher risk of bearing her first child than does a non-working woman. This is unexpected, because childbearing is an opportunity cost to the woman's employment status (Cleland, Onuoha, and Timaeus 1994, Cohen 1998). A similar surprising result was obtained by Kazembe (2009) in his study of fertility levels among Malawian women. As for the type of marital union the women belong to, findings revealed that, whereas women respondents that were not married at the period of the survey show evidence of lower risk of bearing their first child, there is an evidence of higher risk for those in polygamous homes when compared with women respondents in monogamous homes. Also, a significantly lower risk was obtained for women respondents who belong to the households headed by men than to those headed by women.

4.2.2 Baseline and nonlinear effects

Turning our attention to the baseline and to the nonlinear effects of continuous covariates, Figure 2 (a - d) shows the estimated posterior means with their corresponding 95% credible intervals for the nonlinear effects of time to first birth (baseline effect); respondent's age; age at first sexual intercourse and age gap. The baseline effect has a similar pattern for all the models examined. Starting from a relatively lower risk, the baseline effect shows that the risk of bearing a first child increases from age 9 to around the age 13 of years, where it stabilizes till around 45 years of age. Beyond this age, a lowered risk was noticed. Though limited data was available for women who had their first child at age 45 years and above, at these ages, women would have high tendencies of bearing children. Evidently, the effect of respondent's age, age at first sexual intercourse and age gap are nonlinear, and an assumption of a linear effect would have led to a spurious results and interpretations. Results show that risk of bearing a first child is reduced sharply with increase in respondent's age at the period of the survey. Age at first sexual intercourse increases the risk of bearing a first child for women respondents who had their first sexual intercourse before 13 years of age. Thereafter, the risk decreases steadily with increase age at first sexual intercourse. Overall, the age gap curve shows that the risk of bearing a first child is highest when the woman is much older than the household head. Figure 2e presents the surface plot of the posterior mean of the interaction effect of respondents' age and age gap. The figure shows that younger women from household where the head is much older than them are at low risk of bearing a first child. Older respondents, on the other hand, irrespective of the gap between them and that of their household heads, are at higher risk.

Figure 2: Nonlinear effect of (a) age at first birth (baseline effect), (b) respondent's age, (c) age at first sexual intercourse, and (d) age gap; with their corresponding 95% credible intervals. Also included (e) is the surface plot of the posterior mean of interaction effect between respondent's age and age gap

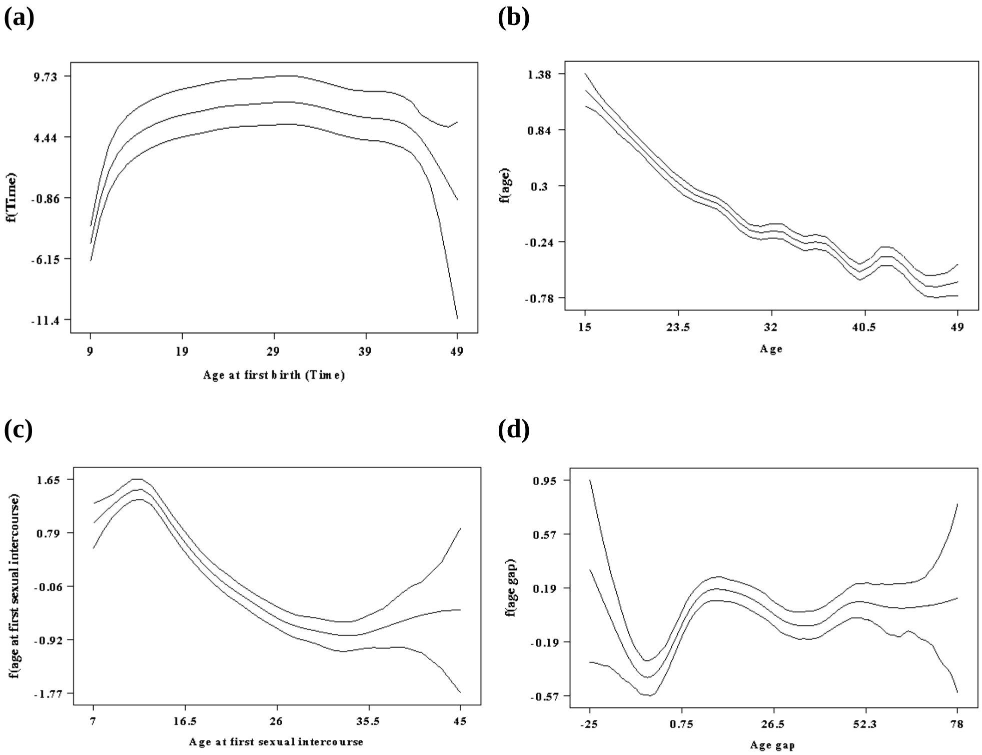
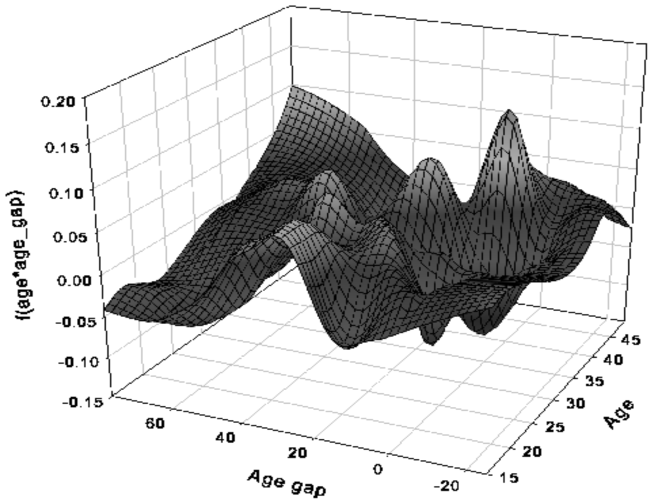


Figure 2: (Continued)

(e)



4.2.3 Spatial effects

Spatial effects of models M_1, M_2 and M_5 are shown in Figure 3(a-f). The left panel of the Figure (Figure 3(a, c & e)) shows the posterior means while the right panel (Figure 3(b, d & f)) displays the corresponding map of location of 95% credible interval, which is used to assess the significance of the spatial effect. From this, states with white colour are significantly associated with higher risk of first birth (i.e. the 95% credible interval lie on the positive side); states with black colour are significantly associated with lower risk (the 95% credible interval lie on the negative side) while the risk is not significant in states with grey colour (the 95% credible interval includes zero). An interesting North-South spatial pattern was noticed in models M_1 and M_2 (Figure 3(a-d)). Controlling for random effects and trends in separate models shows that women respondents in northern part of Nigeria are associated with significant high risk of bearing first child while those in the southern part, with the exemption of Bayelsa state, are associated with low risk. However, the net effect after controlling for the observed individual and community specific variables as well as community random effects shows that only neighbouring Cross River and Ebonyi states have significantly high risks while Lagos, Jigawa, Taraba and Zamfara states are associated with significantly low risks.

Figure 3: Nonlinear spatial effects (a) for model M_1 and (b) its corresponding map of location of 95% credible interval; (c) for model M_2 and (d) its corresponding map of location of 95% credible interval; (e) for model M_5 and (f) its corresponding map of location of 95% credible interval

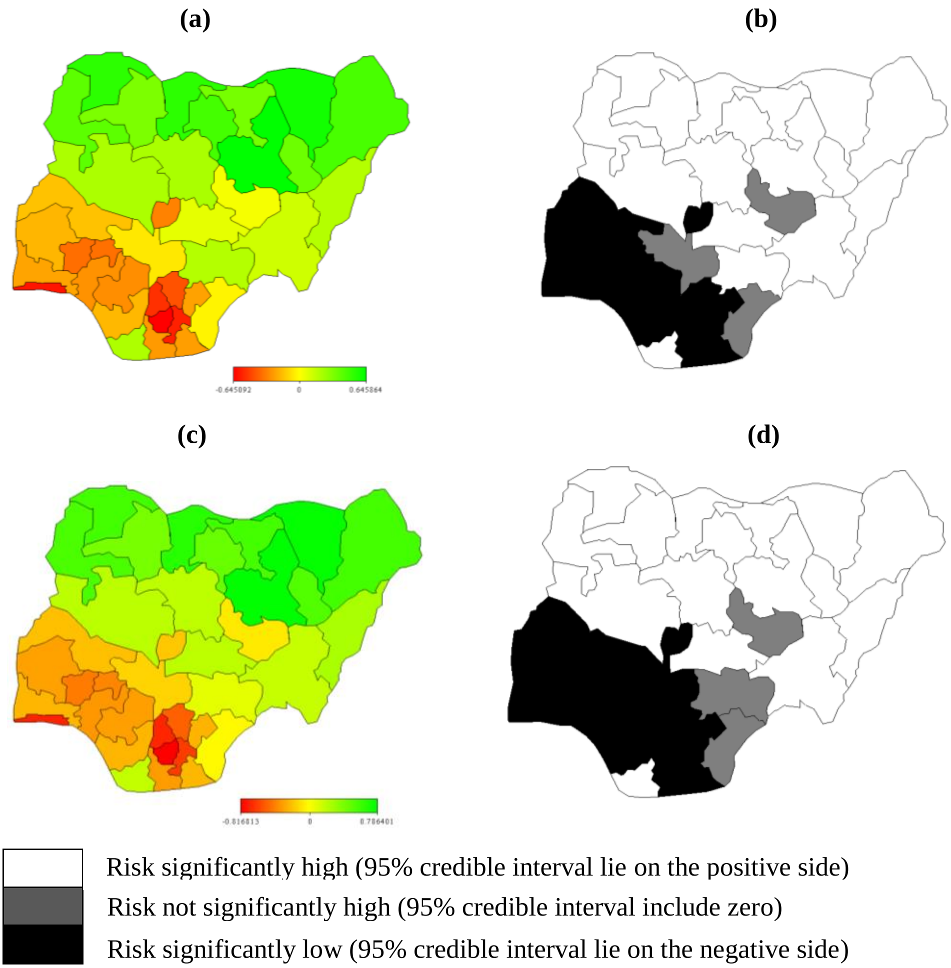
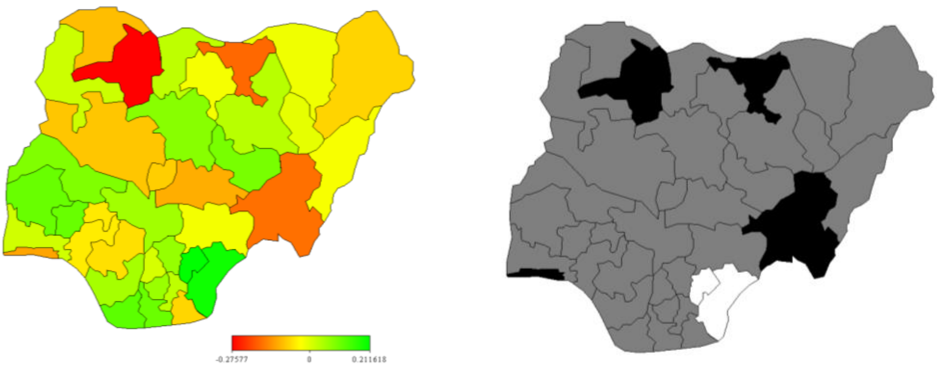


Figure 3: (Continued)

(e) (f)

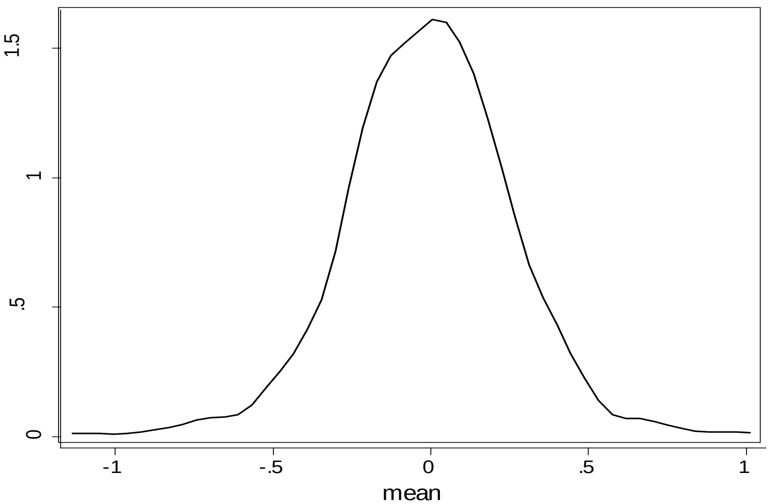


4.2.4 Random effects

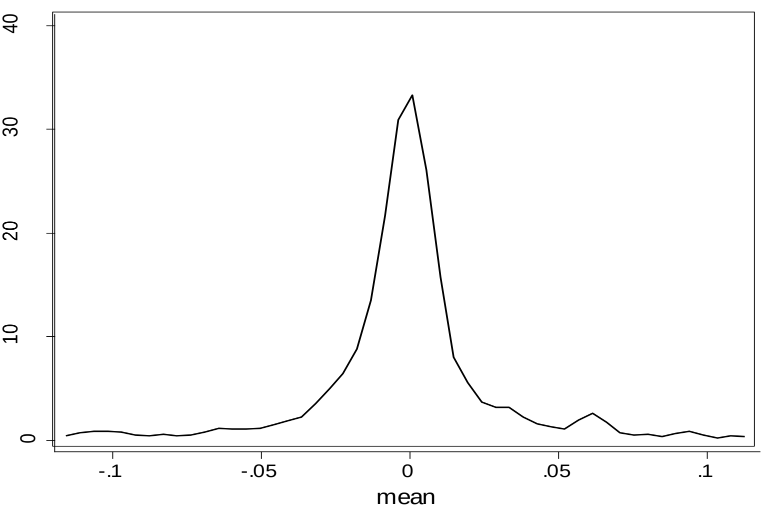
Figure 4 presents the kernel density estimates of the posterior means of (a) community and (b) household random effects. Comparing the two plots shows that the density of the posterior mean of the community random effect has a shape that looks more like a normal distribution than that of the household random effect. This same pattern was observed for the random effects of all the other models considered. An implication of this is that variation among households has more impact on the timing of first birth in Nigeria than it does among communities.

Figure 4: Kernel density estimates for (a) community random effect and (b) household random effect for model M_2

(a)



(b)



5. Discussion of results and conclusion

The age at which childbearing begins influences the total number of children a woman bears throughout her reproductive period, in the absence of any active fertility control. For countries in sub-Saharan Africa, where the prevalence rate of contraception is still low, younger age at first birth tends to increase the number of children a woman will have, thereby hindering the process of fertility decline (Gupta and Mahy 2003, Gyimah 2003). A number of factors at both individual and community levels have been identified to influence timing of first birth. In this paper, geo-additive survival modeling, a technique that permits simultaneously modelling of fixed, nonlinear, heterogeneity and spatial effect within a single framework, was adopted to examine the timing of first birth in Nigeria. Six models of different specifications were employed for this purpose. Estimation was based on Bayesian hierarchical approach. Model performance was ascertained using deviance information criterion (DIC).

The fixed effects analysed in the study allowed demographic relations to be established. A significant trend in timing of first birth was evident in Nigeria. Among the sampled respondents, a decreased risk was observed between 1999 and 2003 while a significantly increased risk was evident between 1999 and 2008. Women who have attained higher education are more likely to delay childbearing than those with lower or no education. A number of studies have similarly observed a positive relationship between women's educational attainment and age at first birth both in developed and developing countries (Maxwell 1987, Martin 1995, Martin and Juarez 1995, Gupta and Mahy 2003, Gyimah 2003). Education brings in a new outlook on life as well as skills for taking advantage of new opportunities. The pathway through which education affects fertility has been highlighted through delay age at marriage, higher contraceptive use, labour force participation, increased bargaining power with the partner, and low regard for high-fertility-sustaining norms. Mboup and Saha (1998) found that in many sub-Saharan Africa countries, women with no formal education (who did not attend school) have two to three children more than women with secondary or higher education. This implies that encouraging Nigerian women to spend more years in school will have an impact on timing of first birth, and consequently lead to a decline in fertility, which recent government policy has targeted. Nigerian government has realized this need, and programmes that can strengthen this are ongoing. Strong and sustained commitment would, however, be required for it to yield the desired results. As Gupta and Mahy (2003) however asserted, focusing on improving women's education alone would not be sufficient to delay timing of first birth. The ultimate goal of women with little or no education in Africa as soon as they are mature is marriage (Ngalinda 1998). This may explain the high risk observed for women with only primary education.

Ethnicity, religion and marital union are among the socio-cultural determinants considered in this study. Previous studies in Nigeria have associated urban marital patterns, ethnicity-specific practices, and religion with high risk of births (Isiugo-Abanihe, Ebigbola, and Adewuyi 1993, Makinde-Adebusoye 2001). Kollehlon (2003) for instance, found that among currently married women, the net fertility of Hausa-Fulani and Yoruba women is lower than that of other women, while that of the Igbo women is higher. Findings on ethnicity in this study confirm the existence of ethnic differentials in risk of first birth in Nigeria. Influence of religion on reproductive related behaviour is reflected in the differences in attitude, belief, and norms regarding birth control and value of children. Similar to findings by Caldwell and Caldwell (1987) where some religions are linked with higher fertility, we found the risk of first birth to be higher among the Catholic women than among those in other religions in Nigeria. It has been argued that Catholic doctrine is pronatalist by favouring large families and rejecting modern methods of birth control, while the Moslems have preference for early and universal marriage (Lucas 1980, Ngalinda 1998). Since the parametric estimate for none of the religious groups was, however, found to be significant, it is expected that as societies develop, reproduction-related behaviour among religious groups in Nigeria would converge, as it has be discovered to do in Ghana (Addai 1999).

Turning to type of marital union, women who are married to men with multiple wives are expected to be much younger than their partners because a husband's age is higher with each additional wife. This exposes the young women to risk of childbirth. It has, however, been argued that in most African societies, polygyny enhances child spacing whereas pregnancies are more frequent in monogamous unions (Ngalinda 1998). With this argument, women in polygamous unions may start childbearing early, but over all, bear fewer children than their counterparts in monogamous unions. On the contrary, women married to the same man may compete to bear children, particularly as in most African societies, women assume low status at marriage, which is elevated by attainment of high fertility. The net effect of polygyny on childbirth can, therefore, be viewed from either direction.

Women who use contraceptives before the birth of their first child are found to be at lower risk of bearing first child compared to those who do not. Unfortunately, as with many other sub-Saharan African countries, contraceptive use is still very low in Nigeria. Though studies have revealed a widespread knowledge of contraceptive methods among Nigerian adolescents and youth, this knowledge does not translate into usage. Family planning is still being regarded as exclusively for married women, and therefore, many family planning clinics are not user-friendly to unmarried women of reproductive age. Discussion about sex and contraception with young or unmarried person is still considered inappropriate, even among health workers (Otoide, Oronsaye, and Okonofua 2001, Abiodun and Balogun 2009, Adebayo et al. 2013). These attitudes need to be reversed and enabling environment suitable for sexually active adolescents and young women, the majority of which are singles, to access contraceptives should be created. This would encourage contraceptive use and, in turn, delay the birth of the first child. Sex education could also be introduced into the school curriculum at primary, secondary and higher education levels.

The estimated pattern of the baseline effect, which remains flat after the initial steady rise indicates that risk of bearing a first child is the same for all women after the age of 13 years. This study reveals that the relationship between age at first sexual intercourse and marriage (for those whose first sexual intercourse occurred in marriage), is positively related with age at first birth. The nonlinear relationship found between the timing of first birth and the continuous covariates considered in this study is an indication that an assumption of linear dependence of these variables would have led to spurious findings, which can misinform policymakers. The structured additive technique allows us to specify the predictor structure in a flexible way such that all relationships between them could be estimated. The steady reduction in the risk of bearing a first child with age at first sexual intercourse is not biologically unusual. Delaying first sexual intercourse might increase age at first birth and hence reduce fertility. However, it may not be plausible to formulate policy aimed at delaying first sexual intercourse in Nigeria. With the existing widespread premarital sexual activities, early age at first birth will continue to be a problem, unless the use of contraceptives to delay first birth is strongly encouraged among adolescents.

Juvenile females were found to have the highest risk of first birth in Nigeria. Economic hardship, urbanization and weakening of traditional structures that informed and regulated young people’s sexual behaviour have been associated with adolescent sexual and reproductive health problems. This situation is worsened due to total lack of a reproductive health education component in the Nigerian school curriculum. It was assumed that such information might encourage promiscuity among adolescents rather than helping them to reduce the consequences of unprotected sex. Matters relating to sex and sexuality are usually shrouded with secrecy, so that adolescent youths find it difficult to access needed information in this regard (Esere 2006, 2008). Similarly, in the Nigerian context, the head of a household is often a male adult irrespective of whether he is the bread-winner or not. If there is no adult male resident, a woman might be the head of the household. In most cases, female-headed households are single-parent households. Women from households headed by females have a higher risk of first birth than their counterparts from male-headed households. This may reflect that women from single-parent household try to imitate the behaviour of their parents by engaging in unprotected sexual activities very early, since a single parent is more likely to have many sexual partners than a married woman. This argument might also be true for households in which the woman is much older than the household head, as in this case she might be the one in control of the house.

Findings from the spatial effects study obviously reveal that age at first birth varies significantly according to geographical locations, i.e., states, in Nigeria. However, after taking into account other relevant determinants, only two states possess higher risk in comparison to others. Surprisingly, none of the two is from the northern part of the country. Analysis of the fixed effects study also reveals a substantial difference among the six geopolitical regions. States in the North East region are associated with significant higher risk of first birth compared to the results of other regions in the country.

In conclusion, the targeted reduction in fertility levels, as contained in recent population policy of Nigeria, can be achieved, if policymakers can broaden the means of achieving this to include a target increase in timing of first birth. While it is more difficult to envision direct policies and programs to increase age at which childbearing begins, delaying first marriage, encouraging women to spend more years in school, as well as encouraging the use of family planning methods by all women of reproductive age, irrespective of their marital status, remain the potentially significant link for delaying first birth. In terms of policy, targeting communities with intervention programmes may not necessarily benefit individual families in lowering levels of fertility. A campaign that is geared towards individual families would achieve a better result. Scarce resources have been identified as a major challenge in implementation of necessary intervention strategies in sub-Saharan African countries, including Nigeria. Findings from this paper will permit policymakers with means of allocating the meagre resources to states where they are crucially needed.

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