Abstract

Unitization of antenatal care services measured by the number of visits is a count variable and, for most developing countries, it is often characterized with excessive zeros due to nonattendance, and over-dispersion necessitating the use of special models for analysis. Zero-inflated negative binomial model was applied to the data from five neighboring West African countries and the usual parametric form of the parameters were extended to structured additive predictors in order to examine spatial patterns in a manner that transcends geographical boundary and nonlinear effects of continuous covariates. Inference was Bayesian based on Markov chain Monte Carlo approach. While results of the socioeconomic and demographic variables largely confirm findings from existing literature, there are significant residual patterns that are unexplained by the variables. In particular, there appears to be a tie transcending boundaries especially among regions of Mali, Niger and northern Nigeria where utilization remains persistently lower.

Keywords: Zero-inflated models, spatial analysis, antenatal care, West Africa, negative binomial
Introduction

The use of antenatal care services during pregnancy has the tendency of impacting on premature delivery as well as infant and maternal mortality (Magadi et al., 2007). When properly utilized, existing conditions that can endanger the developing fetus and the mother are promptly identified for appropriate and timely treatment; chances of utilizing a skilled attendant at birth are enhanced, and the woman approaches pregnancy and childbirth as positive experiences. Against this background, several studies that have examined the usage in many developing countries (Sharma, 2004; Onah et al., 2006; Ali et al., 2010; Habibov, 2011). In sub-Saharan African countries, where maternal and child health indicators are among the poorest, utilization of maternal health services has remained poor for years (MDG Report, 2012). For instance, studies have shown that religious beliefs that undervalue women, the practice of Purdah, the need for women’s reproductive capacity to be regimented by male and the volume of unplanned pregnancies due to low use of contraceptives especially by teenagers contribute to the low usage of maternal health services in the region (Wall, 1998; Magadi et al., 2001; Babalola and Fatusi, 2009; Gayawan, 2014).

Usage of antenatal care services has been studied using the binary logistic model; classifying women into whether or not they had the minimum four attendants during pregnancy as prescribed by the World Health Organization (Navaneetham and Dharmalingam, 2002; Magadi et al., 2007; Habibov, 2011). However, the number of times women attend antenatal clinic is a count variable which naturally should be explored assuming appropriate count models such as the Poison log-linear or negative binomial model. But, several issues common to these data might stretch the assumptions underlying these models and therefore, render their standard forms unsuitable. For instance, for some developing countries, antenatal care data feature a large number of zeros due to that a considerable number of the women make no attendance throughout the period of pregnancy. Other issues include individual unobserved heterogeneity implying over-dispersion and the need to incorporate spatial and nonlinear effects of continuous covariates in addition to the usual parametric effects for categorical covariates in a

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single modeling framework. As a consequence, models for over-dispersion or zero-inflated data offer sensible alternatives (Fahrmeir and Echavarria, 2006; Kazembe, 2013). These models, when combined with semiparametrically structured additive predictors result in rich class of count regression models capable of handling the concerns mentioned above and thereby allowing for quantifying of spatial patterns in the use of antenatal care services.

In this study, we adopt the zero-inflated negative binomial regression model to analyze data on antenatal care attendance in five West African countries. Specifically, we determine socioeconomic and geographical patterns of antenatal care usage among regions of the countries in a manner that transcends geographic boundaries. A study on the use of antenatal care services in the West African sub-region is a burning issue for a number of reasons. As mentioned earlier, the sub-region has one of the worst maternal and child health indicators in the world. Childhood mortality experienced in the West Africa is more than double the share for most countries in the northern and southern Africa (Balk et al., 2004; MDG Report, 2012). Neglect of maternal health services by the people that seem to need them most is considered to be one of the remote causes. Second, the majority of previous studies on antenatal care utilization have either neglected spatial variability except for Gayawan (2014) where data from Nigeria were analyzed, or are based on individual countries thus, making it impossible to observe residual spatial variation across regions of different countries in a manner that goes beyond boundaries. Third, governments of African countries have realized the need to improve accessibility, affordability and quality of maternal healthcare services in the region and, therefore, strenuous efforts are being made in this regard. For instance, governments of some states in Nigeria give incentives to pregnant women who attend antenatal care. Findings from this study could therefore contribute to efforts that encourage utilization of healthcare services during pregnancy in the West African sub-region.
Methods

The model

Consider regression count data \((y_i, w_i), i = 1, ..., n\), where \(y_i\) is the observations on a counting variable \(y\) in this case, number of visits for antenatal care, and \(w_i\) is the observed values of vector of covariate. The standard count data regression model is the log-linear Poisson model where the observations are (conditionally) independent \(y_i | w_i \sim \text{Poisson}(\mu_i)\) with \(\log(\mu_i) = \eta_i\) and \(\eta_i = w_i' \gamma\), a linear predictor, or the negative binomial model. A special case of the Poisson model is the zero-inflated Poisson. To overcome the issue of excess of zeros, zero-inflated models introduce a latent process that ‘inflates’ the number of zero counts. Each observation \(y_i\) is obtained as the product \(y_i = k_i \tilde{y}_i\) of a latent data generating process \(\tilde{y}_i\) and a binary selection process \(k_i\) with probability \(1 - \omega\). Combining zero inflation and over-dispersion result in the zero-inflated negative binomial. These models have a degenerate distribution at zero. We focus on zero-inflated negative binomial model because of its ability to admit over-dispersion (Fahrmeir and Echavarria, 2006; Kazembe, 2013).

Given the predictor \(\eta_i\) and a scale parameter that accounts for over-dispersion \(\delta > 0\), the negative binomial model assumes conditionally independent observations \(y_i | \eta_i, \delta \sim \text{NB}(\theta_i, \delta)\) with probability function given by

\[
P(y_i | \eta_i, \delta) = \frac{\Gamma(y_i + \delta)}{\Gamma(y_i + 1) \Gamma(\delta)} \left(1 + \frac{\delta}{\mu_i}\right)^{-\eta_i} \left(1 + \frac{\mu_i}{\delta}\right)^{-\delta}
\]

for \(y_i \in \mathbb{N} \cup \{0\}\). The mean and the variance are \(E(y_i | \eta_i, \delta) = \mu_i\) and \(V(y_i | \eta_i, \delta) = \mu_i + \mu_i^2 / \delta\), respectively.

The zero-inflated distribution for \(y_i\) is then given by
\[ P(y_i | \eta_i, \delta, \omega) = \begin{cases} 
\omega + (1-\omega) P(\bar{y}_i = y_i | \delta, \eta_i) & \text{for } y_i = 0 \\
(1-\omega) P(\bar{y}_i = y_i | \delta, \eta_i) & \text{for } y_i > 0 
\end{cases} \] (2)

Assuming a negative binomial distribution for \( P(\bar{y}_i | \eta_i, \delta) \), one obtains a zero-inflated negative binomial (ZINB). If the Poisson distribution is assumed, it results in zero-inflated Poisson (ZIP). The density for the ZINB model is given by

\[ P(y_i | \eta_i, \delta, \omega) = \begin{cases} 
\omega + (1-\omega) & \frac{\Gamma(y_i + \delta)}{\Gamma(y_i + 1) \Gamma(\delta)} \left( \frac{\delta}{\mu_i} \right)^{\delta} \left( 1 + \frac{\mu_i}{\delta} \right)^{\delta y_i} & \text{for } y_i = 0 \\
(1-\omega) \frac{\Gamma(y_i + \delta)}{\Gamma(y_i + 1) \Gamma(\delta)} \left( \frac{\delta}{\mu_i} \right)^{\delta} \left( 1 + \frac{\mu_i}{\delta} \right)^{\delta y_i} & \text{for } y_i > 0 
\end{cases} \] (3)

with mean \( E(y_i | \eta_i, \omega) = (1-\omega) \mu_i \) and variance

\[ V(y_i | \eta_i, \delta, \omega) = (1-\omega) \left( \mu_i + \frac{\mu_i^2}{\delta} \right) + \omega (1-\omega) \mu_i^2 \]

With the two parameters \( \omega \) and \( \delta \), the ZINB offers a more flexible way to model the variability of the data when juxtaposed with the negative binomial model.

The likelihood of the ZINB model can be obtained as a product of (3) over all units:

\[ L(y | \eta, \delta, \omega) \propto \exp \left\{ \sum_{y_i=0} \log \left( \omega + (1-\omega) \left( \frac{\delta}{\delta + \mu_i} \right)^{\delta y_i} \right) + \\
\right. \\
+ Z_0 \left( \log (1-\omega) - \log \left( \Gamma(\delta) \right) + \delta \log (\delta) \right) \\
\left. + \sum_{y_i>0} \left( \log \left( \Gamma(y_i + \delta) \right) + y_i \log (\mu_i) - (y_i + \delta) \log (\delta + \mu_i) \right) \right\} \] (4)

where \( Z_0 \) is the number of units with strictly positive response.

To accommodate variables beyond the traditional linear effects, the linear predictor \( \eta_i = w_i' \gamma \) can be extended to structured additive predictors (Fahrmeir and Lang, 2001; Fahrmeir and Echavarria, 2006).
Partitioning covariates into groups of different types $\eta_i$ is defined through the basic structured additive predictor

$$\eta_i = \sum_{j=1}^{p} f_j(x_{ij}) + f_{\text{spat}}(s_i) + w_i'\gamma$$

(5)

In (5), $f_j(x_{ij})$ is the non-linear smooth functions for the metrical covariate $x_{ij}$, $f_{\text{spat}}(s_i)$ is the spatial effects of region of residence and $\gamma$ is a vector of coefficients that determines the linear relationship between the response variable and the categorical covariates, $w$. The spatial component can be split into two parts: one that incorporate structured spatial and the other admits unstructured heterogeneity effect.

Model estimations were carried out following Bayesian approach and appropriate priors were assigned to all the functions and terms. For the scale parameter $\delta > 0$, we assume a weakly informative but proper Gamma prior $\delta \sim G(a,b)$ where $a$ and $b$ are considered as hyperparameters and hyperpriors introduced to them. For the zero inflated parameter $\omega \in [0,1]$, we assumed a flat uniform prior $\omega \sim U[0,1]$. For the fixed effects, we assumed diffuse prior $p(\gamma) \propto \text{const}$ but a weakly informative (highly dispersed) normal prior is also possible. A Bayesian approach of the P-spline introduced by Eilers and Marx (1996) in a frequentist setting was adopted for the nonlinear smooth function. The basic assumption behind this is that the unknown smooth function $f$ of covariate $x$ can be approximated by a polynomial spline of degree $l$ defined on a set of equally spaced knots $x_{\text{min}} = \xi_0 < \xi_1 < \cdots < \xi_{s-1} < \xi_s = x_{\text{max}}$ within the domain of $x$. Such a spline can be written in terms of a linear combination of $m = s + l$ B-spline basis function $B_i$ that is,

$$p(z) = \sum_{i=1}^{m} \alpha_i B_i(z)$$
where \( B(z) \) are B-splines and the coefficients \( \alpha_i \) are further defined to follow a second-order random walk smoothness priors

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

with i.i.d. noise \( \varepsilon_t \sim N(0, \tau^2) \). The variance \( \tau^2 \) controls the smoothness of \( f \) and is jointly estimated with the basis function coefficients. For the structured spatial effects, it was assumed that neighboring sites are more alike than any two arbitrary sites that may be farther apart. Thus, we assumed that two sites \( s \) and \( l \) are neighbors if they share a common boundary. The smoothness prior for the spatial function \( f_{\text{spat}}(s_i) = \beta^\text{spat}_s \) follows an (intrinsic) Gaussian Markov random field (Besag et al., 1991; Rue and Held, 2005). It is given by

\[
\left\{ \beta^\text{spat}_s \mid \beta^\text{spat}_l \neq s, \tau_{\text{spat}}^2 \right\} \sim N \left( \sum_{l \in \delta_s} \beta^\text{spat}_l N_s \tau_{\text{spat}}^2, \tau_{\text{spat}}^2 N_s \right)
\]

where \( N_s \) is the number of adjacent sites and \( l \in \delta_s \) denotes that site \( l \) is a neighbor of site \( s \). The unstructured random effects are i.i.d. random effects \( f_{\text{unstr}}(s) \sim N(0, \phi^2) \).

For the smoothing parameters \( \tau^2, \tau_{\text{spat}}^2 \) and \( \phi^2 \), we assume inverse Gamma priors \( IG(a_j, b_j) \) with hyperparameters \( a_j, b_j \) chosen so that the prior is weakly informative. Common choices for these parameters are \( a_j = 1 \) and \( b_j = 0.005 \) or \( a_j = b_j = 0.001 \). Discussions of our results are based on the latter choice though we did a sensitivity analysis in the applications.

Bayesian inference was based on the analysis of the posterior distribution of the model parameters. Let

\[
\beta = (\gamma', \beta'_1, \ldots, \beta'_k)
\]

be a vector of regression coefficients, \( \tau^2 = (\tau_1^2, \ldots, \tau_m^2)' \) a vector of all variance component and \( \xi = (\delta, \omega)' \) a vector of the scale and zero-inflated parameters and \( y \) denote all observable data. The posterior distribution of the zero-inflated negative binomial model is given by
$p(\beta, \tau^2, \xi | y) \propto L(\beta, \xi) p(\beta, \tau^2) p(\xi)$

with the likelihood $L(\beta, \xi)$ defined as in (4). The posterior distribution is analytically intractable making it difficult for direct inference. Therefore, Markov Chain Monte Carlo (MCMC) sampling from the full conditionals was adopted using a hybrid MCMC sampling scheme. The scheme is a slightly modified Metropolis-Hastings based on iteratively weighted least squares (IWLS) developed for generalized linear mixed model by (Gamerman, 1997). Full details of the updating scheme to generalized additive models can be found in (Fahrmeir and Lang, 2001; Lang and Brezger, 2004).

**Data**

The data set for this study was pooled from the cross-sectional surveys conducted as part of the DHS in 5 West African countries. The countries and year of survey are: Benin (2011-2012), Guinea (2012), Mali (2006), Niger (2012), and Nigeria (2013). These countries are prominent among those with the poorest maternal and child health outcomes and among the least in utilization of maternal health services in the West African region (MDG Report, 2012). In carrying out the surveys, The DHS Program developed standard procedures, methodologies and manuals to guide the survey processes thereby ensuring that the outcomes reflect the true situations and data are comparable across countries and over time (www.dhsprogram.com). The sampling frames were based on the Population and Housing Census conducted by the Agencies and Commissions who were entrusted with such power by the constitutions of their respective countries. The Primary Sampling Units (cluster) were defined on the basis of the Enumeration Areas (EAs) from the Census frames. DHS samples are usually selected using a two-stage stratified design. At the first stage, a number of clusters were selected from the list of EAs. The households to participate in the survey were selected at second stage. All women aged 15-49 years present at the selected households are eligible to participate in the surveys.
Data on antenatal care utilization are contained in the Pregnancy and Post-natal Section of the Women’s questionnaire. Women were asked if they received any antenatal care during pregnancy. If they did, they were required to among others, mention the number of visits made. The histogram of the outcome variable is displayed in Figure 1. The mean number of visits equal to 4.06 and the standard deviation is 4.39, which point to a departure from equi-dispersion (the skweness statistics is 2.36). The median number of attendance is 3 and the range equal 30. The lower and upper quartiles are 0 and 5 respectively.

Only variables that are relatively uniform across the countries were included in the analyses. The following explanatory variables were included: mother’s age at birth, marital duration, educational attainment, parity, working status, wealth index, type of place of residence, partner’s educational attainment, and whether or not the woman listens to radio, watches television and reads newspaper. Region of residence was geo-referenced. The five countries have 41 regions altogether. Figure 2 shows a portion of the map of Africa with the five countries identified.
Fig. 1: A histogram displaying number of visits for antenatal care by women in five West African countries
Results

To analyze the data, we adopt models of various specifications to determine what would be gained or loss by using smooth functions for the continuous covariates. First, we fit the basic model that includes only the geographical regions as random effects. The aim was to determine the crude variations in antenatal care utilization among the countries. The second model includes all the different effects but the continuous covariates were included as linear effects while, in the third, we categorized the continuous variables like other categorical covariates. Finally, smooth functions were used for the continuous variables. We started by analyzing the data for all women respondents (never-married and ever-married). The analyses were then repeated for ever-married respondents. The motive was to enable us assess marital and partner related covariates because such covariates were not available for never-married respondents who got pregnant in the five years preceding the surveys. For all the models, we run 35,000 MCMC iterations and discarded the first 5,000 as burn-in samples, thinned every 10th observation yielding 3,000 samples for parameter estimation. Mixing and convergence were monitored.
by plotting of sampling paths and autocorrelations. For the purpose of model comparison, we adopt the deviance information criterion (DIC), which is useful in Bayesian model selection particularly where the posterior distributions of the models have been obtained by MCMC simulation (Spiegelhalter et al., 2002). In a number of competing models, the one with least value of DIC is considered the best.

Table 1 presents the summary of the diagnostic criteria. For the analyses of all respondents, the model with age as a linear effect has the least DIC value and hence, provides the best fit even though it was a slight improvement over the one with smooth function for age. For ever-married respondents, the model that includes the continuous covariates (age and marital duration) as nonlinear effects has the best fit. Discussions of results will be based on model M4 as it allows us to examine patterns in the continuous covariates that would not be possible as categorical or linear effects.

Table 2 shows the estimates for the categorical covariates, dispersion and zero-inflated parameters with their 95% credible intervals. For both data sets, findings show strong evidences of over-dispersion, while zero-inflation is negligible. Results for all women respondents show that in the West African countries, women who attained at least primary education were significantly more likely to have had more antenatal visits than their counterparts with no education. Women belonging to middle, richer and richest households were more likely to have had more visits that those from the poorest households. However, results show that women from the poorer households were less likely to have gone for antenatal checks during pregnancy compared with those from the poorest families. Women who reside in rural areas were found to have made fewer visits compared with those in the urban centers. Findings further show that pregnant women who could access either radio or television at least once a week had more visits than those without the opportunity. However, findings on newspaper do not indicate significant difference. Utilization was also higher for working mothers compared with those not working but, findings based on parity was not significant.
Results for ever-married respondents presented at the right hand panel of Table 2 are similar to those of all women respondents except that estimate for women who had primary education was not significant while those with between 2 and 3 children had significantly lower attendance compared with women of first parity. As expected, women whose partners had at least primary education made significantly higher number of antenatal visits than those whose partners had no education.

Results for the nonlinear effects of age at marriage and marital duration are presented in Figure 3. Also included are the 95% credible intervals. For all women respondents, results show that women below age 25 years and those above 40 years were less likely to have utilized the services during pregnancy. For ever-married respondents, utilization increased for every unit increase in age until around age 45 years from where it dropped. For marital duration, findings show that utilization of antenatal care services reduce as women grow older in marriage.

Figure 4(a-f) presents the results for the spatial effects. The left panel shows the maps of posterior means while the right panel shows the maps of credible intervals used in assessing the significance of the estimates. From the maps of posterior intervals, black (white) shadings signify significantly lower (higher) utilization of antenatal services while estimates for regions in gray shading are not significant. Findings from the crude distribution show that utilization of antenatal care services was significantly higher among women in southern and central Nigeria, and in southern Benin. However, utilization was lower in most parts of Niger, Mali, and in northwestern Nigeria. But, a portion of the observed variations in the crude pattern was explained when covariates were included. The results show that southeast and southwest Nigeria, with southern Benin record significantly higher utilization while utilization was lower among women who reside in Agadez and Diffa in the northeastern regions of Niger, and in Mopti, Segou, Tombouctou, Kidal, and Gau regions of Mali. Estimates for the other regions are not significant. In the case of ever-married respondents, utilization was significantly higher in southwest, southeast and central Nigeria; southern Benin (Collines, Atlantique, Oueme, Mono, Kouffo, and Zou regions) and in
central and eastern Guinea (Kankan, Faranah, Mamou, and Labe regions). On the contrary, utilization by ever-married women was lower in the entire Mali, Niger, northeast and northwest Nigeria, and in Borgou region of Benin.

**Discussions of results and conclusion**

The sparse attendance for antenatal care services in developing countries especially in West African countries has necessitated the use of specialized models. To this end, this study proposes the use of zero-inflated models to account for the high number of zero and the resulting over-dispersion in the distribution. Extending the parameters of the model to the notion of structured additive regression allows for examination of variables of different types within a single framework. The spatial autocorrelation analysis assumes neighboring structure that assesses the extent of interrelation among neighboring countries rather than treating the regions as though they were independent of one another.

The spatial analysis reveals dissimilar pattern that demonstrates that, among the five West African countries considered, utilization of antenatal services was lower in northern Nigeria, Mali and Niger particularly among the ever-married respondents. The pattern points to the influence of some variables not accounted for in the study, which could have strong spatial structure. This is more evident in the case of Mali where, after controlling for the measured demographic and socioeconomic variables, the observed spatial pattern from the crude data remained unaltered. Such factors as perceived quality of care offered or distance to antenatal care service providers could result in huge variations in the use of the services between locations. Also, variations in cost of the services can be grounds for variations in the utilization between locations as women who are made to pay for the services may not be well motivated to go for the required check-ups. Therefore, it may be worthwhile for governments especially in regions with low usage, to consider addressing these issues in order to buoy up pregnant women attendance for antenatal care services. Efforts that could sustain utilization are also required in regions where numbers of visits are high.
The findings on most of the categorical and continuous covariates are in concord with what has been reported in the literature. For instance, as further confirmed by this study, educated women and those from well-to-do homes are more likely to have made the required number of visits for antenatal care. These women are in better positions to know the essentials of having the required number of visits and how the systems providing the services function, thus, they take full advantage of it (Celik and Hotchkiss, 2000; Sharma, 2004; Habibov, 2011; Gayawan, 2014). The influence of education might have contributed to the north-south divide pattern exhibited for Nigeria as it is well known that women (and equally men) from southern Nigeria are better educated than their counterparts in the northern fringe, a factor that has been contributing to lopsided health indicators in the country (Gayawan and Turra, 2015). Women in urban centers are likely to have antenatal care providers within reach and in environments with better road networks than those in rural areas who are faced with paucity of healthcare providers and poor road networks; situations that are paramount in most West African nations. There is therefore the need for reconciliation of needs in budgetary allocations to cater for the needs of residents of rural communities. The findings on access to mass media which reveals that, unlike newspaper, women who listened to radio and watched television have high potentials for utilizing antenatal services are expected because these two mediums are usually handy even to people in rural areas and information that could benefit women and children are translated into local dialects in radio and television programs. Regarding working status we found working-women to be favored in the utilization of the services, similar pattern has been reported in other developing countries (Sharma, 2004; Regassa, 2011).

The nonlinear effects of age have shown that women who experience pregnancy early in life and older women have lower likelihoods of utilizing antenatal care. These are likewise consistent with previous findings (Onah et al., 2006; Hazemba and Siziya, 2008; Gayawan, 2014). Whereas experience and confidence gained from previous pregnancies might account for low utilization by older women, inexperience in pregnancy care may possibly be a cause for the younger ones. Young women who have
premarital pregnancy may also fail to initiate appropriate care early enough thus, reducing the possible number of visits they would have. Women of high parity could bank on previous capability, lack adequate resources or lose interest due to negative encounter with healthcare providers during previous pregnancies and, therefore be unwilling to attend antenatal care. The confounding effects of parity could account for the inverse relationship between number of visits and marital duration.

The capacity of the adopted methods to control for zero-inflated and over-dispersion in the data guarantees the accuracy of the estimates. Neglecting these would have led to underestimations of the standard errors which would have led to erroneous assessment of the significance of the parameters (Fahrmeir and Echavarria, 2006). By extending the parameters to structured additive models, we are able to detect socioeconomic and spatial patterns of antenatal care utilization than reliance on classical linear approaches with regional dummy variables. Even though the analysis could not identify all variables that account for the spatial structure and the cross-sectional nature of the data does not permit for causal inference, the findings are pinpointing and can aid in generating hypotheses on the underlying reasons for the observed spatial patterns. Further, the results could be useful for planning purposes which is a pivot issue in policy circles that aim at focusing the allocation of resources to the most needed areas. It is imperative however to mention that the smallest spatial unit in the analysis is the region which is naturally made up of many geographical entities and as such, within-area variability is expected. A further analysis that considers smaller units within the regions could be useful in unraveling variations at a more localized level.
Table 1: Coefficients of the deviance information criterion (DIC)

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<th>Model</th>
<th>All respondents</th>
<th>Ever-marry respondents</th>
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<tbody>
<tr>
<td>M1</td>
<td>21123.719</td>
<td></td>
</tr>
<tr>
<td>M2</td>
<td>20086.837</td>
<td>20088.739</td>
</tr>
<tr>
<td>M3</td>
<td>20092.995</td>
<td>20025.377</td>
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<td>M4</td>
<td>20089.782</td>
<td>20017.876</td>
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Table 2: Estimated posterior means and 95% credible intervals

<table>
<thead>
<tr>
<th>Variable</th>
<th>All women respondents</th>
<th>Ever-married respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Posterior mean</td>
<td>Credible interval</td>
</tr>
<tr>
<td>Constant</td>
<td>1.357</td>
<td>1.291, 1.422</td>
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<tr>
<td>Woman’s education</td>
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<td></td>
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<tr>
<td>No education</td>
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<tr>
<td>Primary</td>
<td>0.042</td>
<td>0.011, 0.073</td>
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<td>Secondary &amp; Higher</td>
<td>0.153</td>
<td>0.115, 0.191</td>
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<td>Wealth index</td>
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<tr>
<td>Partner’s education</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No education</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Primary</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Secondary &amp; Higher</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dispersion parameter ((\delta))</td>
<td>0.320</td>
<td>0.315, 0.324</td>
</tr>
<tr>
<td>Zero-inflated parameter ((\omega))</td>
<td>0.0004</td>
<td>0.000, 0.001</td>
</tr>
</tbody>
</table>
Fig. 3: Nonlinear effects of (a) mother’s age at birth (all women respondents), (b) mother’s age at birth (ever-married respondents), and (c) marital duration
Fig. 4: Spatial effects of (a) crude attendance at ante natal care (all women respondents), (b) its 95% credible interval, (c) after adjusting for covariates (all women respondents), (d) its 95% credible interval, (e) after adjusting for covariates (ever married respondents), and (f) its 95% credible interval.
References


