**American Journal of Theoretical and Applied Statistics**
2023; 12(5): 110-116
http://www.sciencepublishinggroup.com/j/ajtas
doi: 10.11648/j.ajtas.20231205.12
ISSN: 2326-8999 (Print); ISSN: 2326-9006 (Online)

# Bayesian Binary Quantile Regression for Modelling Injectable Contraceptive Uptake Among Child Bearing Women in Kenya

**Dan Kipkosgei Kogei*, Anthony Wanjoya, Joel Chelule, Lena Onyango**

Department of Statistics and Actuarial Sciences, Jomo Kenyatta University of Agriculture and Technology (JKUAT), Nairobi, Kenya

### Email address:

dankipkosgei6@gmail.com (Dan Kipkosgei Kogei), awanjoya@gmail.com (Anthony Wanjoya), jchelule@jkuat.ac.ke (Joel Chelule), lenaonyango75@gmail.com (Lena Onyango)

*Corresponding author

### To cite this article:

Dan Kipkosgei Kogei, Anthony Wanjoya, Joel Chelule, Lena Onyango. Bayesian Binary Quantile Regression for Modelling Injectable Contraceptive Uptake Among Child Bearing Women in Kenya. *American Journal of Theoretical and Applied Statistics*. Vol. 12, No. 5, 2023, pp. 110-116. doi: 10.11648/j.ajtas.20231205.12

**Received**: August 31, 2023; **Accepted**: September 14, 2023; **Published**: September 27, 2023

**Abstract:** Injectable contraceptives are methods of contraception that is administered through injection. In the recent times, injectable contraceptives have been preferred to other modern contraceptives by child bearing women which implies that there are factors contributing to this surge in the usage of injectable contraceptives. Currently in Kenya, injectable contraceptives are the most used methods of modern contraceptives. In addition, most studies have used logistic regression to model modern contraceptives but logistic regression focuses only in conditional mean (central quantile of the response variable). Bayesian quantile regression involves application of Bayesian techniques to quantile regression where the continuous Asymmetric Laplace Distribution (ALD) is used to formulate the likelihood used for posterior estimation. The main objective of this study was to model injectable contraceptive uptake among child bearing women using Bayesian binary quantile regression in Kenya. The study used nationally representative cross sectional secondary data obtained from PMA (Performance monitoring for Action) which was collected from November to December 2021 targeting women of child bearing age (15-49 years). Data analysis was done using R software. Bayesian quantile regression model parameters were estimated using Markov Chain Monte Carlo (MCMC) Gibbs sampling for 5 different quantiles (0.10, 0.25, 0.50, 0.75 and 0.95) and convergence diagnostics was performed to assess the convergence of generated MCMC posterior samples to target posterior distribution. Convergence diagnostics are very crucial in Bayesian statistics to ensure accuracy and reliability of the inferences drawn from model posterior distribution. Convergence was achieved based on Gelman and Rubin's diagnostics for all parameters being less than 1.1 implying accuracy of model parameters. The uptake of injectable contraceptives was found to be greatly influenced by wealth quintile, level of education, marriage status of woman and the number of birth events to a woman. More specifically, women in highest wealth quintile had lower likelihood of using injectable contraceptives as compared to those in the lowest quintile, those who are widows, divorced and never married had lower likelihood of using injectable contraceptives compared to the currently married women, women with primary and secondary education levels were more likely to use injectable contraceptives compared to women with no education, increase in the number of birth events negatively influences the uptake of injectable contraceptives. This study concluded that marital status, birth events, education level and wealth quintile are significant predictors of injectable contraceptive uptake in Kenya.

**Keywords:** Injectable Contraceptives, Child Bearing Women, Bayesian Binary Quantile Regression, MCMC, Convergence Diagnostics

## 1. Introduction

Contraceptives in reproductive health are usually drugs, devices or surgery used to prevent or avert pregnancy. The use of contraceptives is an efficient mode to avert pregnancy among married women and those in intimate relationships.

Injectable contraceptives which involves an injection into the body are among the modern methods of contraception which have been widely utilized in many countries. Other forms of modern contraceptives includes pills, male and female condoms, implants, sterilization, inter uterine devices (IUDs), Emergency Contraception (EC) among others [1]. These forms of contraception have been widely used in the recent times compared to traditional methods of contraception. In addition of preventing pregnancies, contraceptives also can help in reducing the number of both maternal and infant mortalities which might result from unintended pregnancies therefore making women of reproductive age to have no option but to use contraceptives.

Contraceptive Prevalence Rates (CPR) are different for countries for instance, among the three East African countries; Kenya, Rwanda and Uganda, the CPRs among women of child bearing age are 58%, 53% and 30% respectively[2] implying that Kenya has the highest CPR. This is attributed to the fact that there has been feasible advancement in the consumption of contraceptives in Kenya [3]. From these advancements over the years, the uptake of injectables as a method of contraception has been higher as compared to other modern methods [4].

Quantile regression is a type of regression analysis used to model a set of independent variables and specific quantiles of the outcome or the response variable [5, 6]. Quantile of response variable is a value that divides the response variable into portions and in particular, quantile of binary response variable, is a value that divides the response variable into parts based on the probability of positive outcome [7, 8]. Quantile regression is more powerful than the mean regressions which are mainly based on the conditional mean of the response outcome [8]. Applications of Bayesian methods to binary quantile regression results into more robust results because of involvement of the aspects of prior and posterior distributions of model parameters and in particular parameter estimation via Gibbs sampling is very efficient. Various comparative studies have shown that Bayesian quantile regression outperforms the frequentist quantile regression [9, 10].

Tigabu et al [11] used multivariate logistic regression analysis to evaluate various socio economic and religious disparities in various forms of modern contraceptives in Oromia, Ethiopia. They found that injectable contraceptives were the most preferred method among all the modern contraceptive methods for married women. In addition, the Orthodox Christian married women had higher likelihood of using any form of modern contraceptives when compared to Muslim women [11]. The catholic women and the protestants had no significant relationship with any form of modern contraceptives. Further study revealed that a woman with an employed partner was more likely to use any form of modern contraceptive.

Various factors have been attributed to the uptake of modern contraceptives. Beson et al [12] utilized logistic regression to identify prevalence, know how level and the predictors of modern contraceptive usage among child bearing women in Ghana. Injectable contraceptives was the most used form of modern contraceptive [12]. They found that the formal level of education did not significantly predict the use of modern contraceptives in Ghana. Among the strong predictors of modern contraceptives use were; women attitude towards contraceptive use where those who had positive attitudes had higher likelihood than those with negative attitudes [12]. Also religion predicted the use of modern contraceptives whereby women who value their religious view about contraceptive use were less likely to use any form of modern contraceptives.

There is only one study in Kenya which has been done in regard to the injectable contraceptive usage in Kenya [13]. This study used the multiple logistic regression to determine various factors that can affect injectable contraceptive use in Kenya. The outcome of this study revealed that some variables such as the number of birth events, place of residence, wealth status, marital status of the woman and the highest education level attained by a woman were very significant predictors of the use of injectable contraceptives as a contraceptive method [13].

From the studies above, it is clear that the injectable contraceptives are the most preferred methods among all the modern forms of contraception and that logistic regression has been only used to determine several factors influencing modern contraceptive usage. Logistic regression is based on the mean value of the response variable [8] which does not show covariate effects in other quantiles of the response variable. Therefore a more robust Bayesian binary quantile regression method was utilized in this work in modelling the use of injectable contraceptives in Kenya.

# 2. Methods

### *2.1. Data and Study Variables*

The study used nationally representative cross-sectional data obtained from the Performance monitoring for Action (PMA) which was collected November to December 2021. The study targeted women of reproductive age, that is, age 15 to 49 years from eleven counties in Kenya which were namely; Kericho, Kiambu, Kilifi, Kitui, Bungoma, Kakamega, Nandi, Nairobi, Nyamira, Siaya and West Pokot. A sample of 4677 child bearing women were included in this study. The response variable was use of injectable contraceptives coded as 1 for women using injectable contraceptives and 0 for women using other methods of contraception. The explanatory variables were age of the woman, number of birth events, education level, wealth quintile, marital status, religious background of the woman and place of residence. Statistical analysis was done using R version 4.2.3 where the package bayesQR was used for Bayesian binary quantile regression and CODA package was used to test the convergence diagnostics.

### *2.2. Bayesian Binary Quantile Regression*

#### *2.2.1. Posterior and Parameter Estimation*

Bayesian Quantile regression involves using Bayesian methods in quantile regression where the Asymmetric Laplace

Distribution (ALD) is used to formulate likelihood function for estimating posterior distribution of the model parameters [14]. Variable x is said to be Asymmetric Laplace Distributed if its density function is given by;

$$f(x|\mu,\sigma,q) = \frac{q(1-q)}{\sigma}\exp\left\{-\rho_q\left(\frac{x-\mu}{\sigma}\right)\right\} \quad (1)$$

Where $\mu$ is the location parameter, $\sigma$ is the scale parameter which is usually taken as 1 for simplicity, $q$ is the skewness parameter or the quantile and $\rho_q(x) = x(q - I(x<0))$ is the loss function $I(.)$ being indicator function.

According to Benoit & Van den Poel [7], the binary quantile regression model is given by;

$$y_i^* = x_i'\beta(q) + \varepsilon_i \quad (2)$$

$$y_i = \begin{cases} 1: y_i^* > 0 \\ 0: y_i^* \le 0 \end{cases}$$

Where $y_i^*$ is a latent variable introduced to determine the observe binary response variable $y_i$, $x_i$ is a p × 1 vector of explanatory variables, $\beta(q)$ is p × 1 regression coefficient vector according to the respective quantiles q and $\varepsilon_i$ is the random error term, i=1,…, n. Note that $\beta(q)$ means coefficient of parameters in different quantiles for instance, coefficients of a variable at two different quantiles are $\beta(q_1)$ and $\beta(q_2)$.

The variables $y^* = y_1^*, y_2^*, \ldots y_n^*$ introduced in equation (2) according to Benoit [7] are asymmetric Laplace distributed with the distribution function given as;

$$f(y^*|\mu,\sigma,q) = \frac{q(1-q)}{\sigma}\exp\left\{-\rho_q\left(\frac{y^*-\mu}{\sigma}\right)\right\} \quad (3)$$

Where $\mu = x_i'\beta(q)$

The joint posterior distribution of the unobserved parameters $\beta(q)$ and $y^*$ given the quantile of interest $q$ and data X is proportional to the product of the prior and the likelihood function given by Benoit & Van den Poel [7];

$$p(\beta(q), y^*|x,q) \propto p(\beta(q))\prod_{i=1}^{n}\{I(y_i^*>0)I(y_i=1) + I(y_i^* \le 0)I(y_i=0)\}F_{y^*}(y_i^*; x_i'\beta(q),1,q) \quad (4)$$

Where $p(\beta(q))$ is the regression coefficient prior distributions and $I(.)$ denotes the indicator function. The posterior distribution of the model parameters can be deduced from equation (4) as;

$$p(\beta(q)|y^*,x,\tau) \propto p(\beta(q))\prod_{i=1}^{n} F_{y^*}(y_i^*; x_i'\beta(q),1,q) \quad (5)$$

Equation (5) denotes the posterior distribution of the parameters of binary quantile regression. It is a very complex posterior to be sample directly and hence MCMC methods are utilized in this case to generate samples from this type of posterior. Usually Gibbs sampling technique is used to draw samples from this complex conditional posterior distribution. After posterior specification, Bayesian binary quantile regression model parameters are then estimated using the following MCMC-Gibbs sampling steps according to Dichandra et al [19];

Specify the quantile of interest to be estimated, $q$.

Determine the initial values of all the k parameters; $\beta(q)^{(0)} = \left(\beta(q)_1^{(0)}, \beta(q)_2^{(0)}, \ldots, \beta(q)_k^{(0)}\right)$.

Generate the posterior samples as;

$$\beta(q)_1^{(1)} \sim p\left(\beta(q)_1 | \beta(q)_2^{(0)}, \beta(q)_3^{(0)}, \ldots, \beta(q)_k^{(0)}, y^*, q\right)$$

$$\beta(q)_2^{(1)} \sim p\left(\beta(q)_2 | \beta(q)_1^{(0)}, \beta(q)_3^{(0)}, \ldots, \beta(q)_k^{(0)}, y^*, q\right)$$

…

…

…

$$\beta(q)_k^{(1)} \sim p\left(\beta(q)_k | \beta(q)_1^{(1)}, \beta(q)_2^{(1)}, \ldots, \beta(q)_{k-1}^{(1)}, y^*, q\right)$$

Repeat step 3 n times for all parameters at different quantile levels at each iteration n to obtain; $\beta(q)_k^{(n)} \sim p\left(\beta(q)_k | \beta(q)_1^{(n)}, \ldots, \beta(q)_{k-1}^{(n)}, \ldots, \beta(q)_k^{(n-1)}, y^*, q\right)$

The sample sequences obtained from steps 3 and 4 are;

For the first parameter $=\left\{\beta(q)_1^{(1)}, \beta(q)_1^{(2)}, \beta(q)_1^{(3)}, \ldots, \beta(q)_1^{(n)}\right\}$

For the second parameter $= \left\{\beta(q)_2^{(1)}, \beta(q)_2^{(2)}, \beta(q)_2^{(3)}, \ldots, \beta(q)_2^{(n)}\right\}$

…

…

…

For the last $k^{th}$ parameter$=\left\{\beta(q)_k^{(1)}, \beta(q)_k^{(2)}, \beta(q)_k^{(3)}, \ldots, \beta(q)_k^{(n)}\right\}$

These sample sequences are then averaged empirically to obtain the Bayesian parameter estimates for the k parameters; $\beta(q)_1,\ \beta(q)_2, \beta(q)_3, \ldots, \beta(q)_k$

Note that the superscripts are the iterations while the subscripts are parameters.

### *2.2.2. Convergence Diagnostics*

Convergence diagnostics are usually very important for testing whether the samples drawn from the posterior distribution are really converging to the posterior distribution of interest. The commonly used formal method for assessing convergence diagnostic is the Gelman and Rubin diagnostic [15]. The Gelman and Rubin's diagnostic works in the same like analysis of variance. The Gelman and Rubin's diagnostic for each model parameter is found by running two or more chains with differed beginning values. Let $\beta(q)_{ij}$ be a parameter for i iteration in chain j for a given quantile q then the variance of within chain mean is computed as;

$$Wc = \frac{1}{m(n-1)}\sum_{j=1}^{m}\sum_{i=1}^{n}\left(\beta(q)_{ij} - \overline{\beta(q)_J}\right)^2 \quad (6)$$

Where m denotes the chains, n represents the iteration number in each chain and $\overline{\beta(q)_J}$ is the mean within the chain.

Compute the variance between the chains by;

$$Bc = \frac{n}{m-1}\sum_{j=1}^{m}\left(\overline{\beta(q)_J} - \overline{\beta(q)}\right)^2 \quad (7)$$

Where $\overline{\beta(q)}$ denotes the grand mean.

Next is to find the estimate of the pooled variance denoted by $\widehat{Vp}$ using the following formula;

$$\widehat{Vp} = \frac{(n-1)}{n} Wc + \left(1 + \frac{1}{m}\right) \frac{Bc}{n} \quad (8)$$

After obtaining the mean of the within chain variance and the estimated pooled variance, we then compute the ratio of pooled variance and the variance within chain denoted by $\widehat{Rp}$ as;

$$\widehat{Rp} = \frac{\widehat{Vp}}{Wc} \quad (9)$$

The $\widehat{Rp}$ can be modified to form the Potential Scale Reduction Factor (PSRF) because when estimating the pooled variance, the errors due to sampling might occur [Du]. Therefore the PSRF or the modified $\widehat{Rp}$ is given by;

$$PSRF = \frac{df}{df-2} \frac{\widehat{Vp}}{Wc} \quad (10)$$

Where df denotes the degrees of freedom estimated for the approximate t student distribution and $\frac{df}{df-2}$ denotes the term used for adjusting $\widehat{Rp}$. The PSRF less than 1.1 indicates that the chains has converged in distribution to the target posterior distribution [15] and that the model parameters are reliable for making inferences. This is a very crucial step in any Bayesian analysis has it allow one to make valid inferences. If chains does not converge then running them for longer number of iterations is the remedy [15].

# 3. Results

From table 1, for marital status, about 37% and 36% of the married and those women living with a man as if married were found to be using injectable contraceptives while about 19% of those who are not married were users of injectable contraceptives. Among women with primary level of education, about 38% of them uses injectable contraceptives, about 35% of those with post primary vocational uses injectable contraceptives, about 32% of those with secondary education uses injectable contraceptives, while about 25%, 17%, and 12% of those with college education, no education and university education respectively are users of injectable contraceptives. Regarding wealth quintile of a women, women who are in lower wealth quintile had higher proportion to use injectable contraceptives about 38% while among women with highest wealth quintile had the lowest proportion of using injectable contraceptives. Regarding women place of residence, among those living in rural areas, about 34% of them uses injectable contraceptives while 30% of those residing in urban areas are users of injectable contraceptives. For religious background of women, about 34% of those who are Protestants uses injectable contraceptives, about 39% of the Muslim women uses injectable contraceptives while those from catholic exhibited lower proportion about 28%. From table 2 the mean age of all women included in the study was 31.6 years while the mean number of birth events born to a woman was about 3 children.

***Table 1.*** *Proportion of women using injectable contraceptives and other methods for categorical variables.*

| Variable | Proportion using injectables and other methods | |
|---|---|---|
| | Users | Users of other methods |
| Marital Status | | |
| Married | 37% | 63% |
| Living with a man | 36% | 64% |
| Divorced | 32% | 68% |
| Widow | 25% | 75% |
| Not married | 19% | 81% |
| Education Level | | |
| No education | 17% | 83% |
| Primary level | 38% | 62% |
| Vocational after primary | 35% | 65% |
| Secondary A level | 32% | 68% |
| College level | 25% | 75% |
| University level | 12% | 88% |
| Wealth Quintile | | |
| Lowest quintile | 35% | 65% |
| Lower quintile | 38% | 62% |
| Middle quintile | 34% | 66% |
| Higher quintile | 34% | 66% |
| Highest quintile | 24% | 76% |
| Residence | | |
| Rural | 34% | 66% |
| Urban | 30% | 70% |
| Religion | | |
| Protestant | 34% | 66% |
| Catholic | 28% | 72% |
| Muslim | 39% | 61% |
| Other | 31% | 69% |
| No religion | 35% | 65% |

***Table 2.*** *Descriptive statistics for numerical variables.*

| Variable | Range | Mean | Standard Deviation |
|---|---|---|---|
| Age | Minimum: 15; maximum: 49 | 31.6 | 8.39 |
| Birth events | Minimum: 0; maximum: 14 | 3 | 2 |

The seven explanatory variables were subjected to the bidirectional stepwise regression for selecting variables to be used in the final Bayesian binary quantile regression. Only the number of birth events, education level wealth quintile and the marital status of the woman Were retained in the final stepwise model and therefore this variables were used in estimating the Bayesian binary quantile regression model. The Bayesian binary quantile regression model was estimated for five different quantiles, the lower quantiles (0.10 and 0.25), the central quantile (0.5) and the upper quantiles (0.75 and

0.95). We used the multivariate diffused normal priors in all model parameters, $N(0,100)$ and the estimation of all model parameters was done using the MCMC Gibbs sampling with 27000 iteration and discarding 2000 iterations as initial burn-in.

***Table 3.** Bayesian binary quantile regression parameter estimates for lower and central quantiles with Bayesian Credible Intervals.*

| Parameters | $q$ =0.1 | $q$ =0.25 | $q$ =0.50 |
|---|---|---|---|
| Intercept | -10.031 (-13.446, -6.798) | -3.380 (-4.460, -2.038) | -0.918 (-1.801, -0.145) |
| Wealth Quintile: lower | 0.714 (-0.528, 1.911 ) | 0.269 (-0.250, 0.795) | 0.162 (-0.083, 0.414) |
| Wealth Quintile: middle | -0.156 (-1.378, 1.198) | -0.017 (-0.548, 0.475) | -0.003 (-0.255, 0.263) |
| Wealth Quintile: higher | -0.847 (-2.058, 0.425) | 0.314 (-0.856, 0.203) | -0.156 (-0.427, 0.115) |
| Wealth Quintile: highest | -3.396 (-5.023, -1.132) | -1.349 (-1.945, -0.722) | -0.680 (-0.996, -0.337) |
| Education Level: primary | 4.517 (1.592, 7.479) | 1.885 (0.623, 3.301) | 0.979 (0.286, 1.817) |
| Education Level: vocational | 2.436 (-1.644, 6.174) | 1.059 (-0.757, 2.858) | 0.566 (-0.359, 1.549) |
| Education Level: secondary level | 3.550 (0.618, 6.465) | 1.492 (0.235, 2.986) | 0.771 (0.044, 1.611) |
| Education Level: college level | 2.212 (-0.678, 5.486) | 0.942 (-0.527, 2.505) | 0.515 (-0.249, 1.348) |
| Education Level: university level | -2.627 (-7.375, 1.780) | 1.885 (-0.623, 3.301) | -0.555 (-1.634, 0.503) |
| Marital Status: living with man | -0.270 (-1.839, 1.089) | -0.119 (-0.749, 0.486) | -0.056 (-0.362, 0.233) |
| Marital Status: divorced | -1.475 (-2.764, -0.241) | -0.578 (-1.224, 0.038) | -0.293 (-0.601, 0.013) |
| Marital Status: widow | -3.100 (-7.164, 0.346) | -1.255 (-2.590, -0.078) | -1.673 (-1.399,-0.038) |
| Marital Status: not married | -6.302 (-7.970, -4.602) | -2.524 (-3.155, -1.917) | -1.259 (-1.559, -0.969) |
| Birth Events | -0.519 (-0.747, -0.257) | -0.204(-0.290, 0.119) | -0.104 (-0.153, -0.056) |

$q$ Denotes the quantile, Bayesian Credible Intervals are in brackets

Table 3 displays the Bayesian parameter estimates with the respective Bayesian Credible Intervals (BCI's) for the lower estimated quantiles (0.10 and 0.25) and the central quantile. Regarding the wealth status, has exhibited by BCI's not containing zero only one category (highest wealth quintile) was significant in describing the difference in the uptake of injectable contraceptives with the reference category (lowest quintile) while all other wealth quintiles were not significant in explaining injectable contraceptives use. For education attainment of women, primary and secondary education levels were significant in explaining the difference in the usage of injectable contraceptives with reference category (no education category) for all the estimated lower and middle quantiles. For only the first estimated quantile, divorced marital status was significant in explaining the use of injectable contraceptives while widow and never married categories were significant for all the estimated lower and upper quantiles. Number of birth events also was found to be greatly influencing the uptake of injectable contraceptives at all the estimated lower and upper quantiles.

***Table 4.** Bayesian binary quantile regression parameter estimates for upper quantiles with Bayesian Credible Intervals.*

| Parameters | $q$ =0.75 | $q$ =0.95 |
|---|---|---|
| Intercept | 0.578 (-0.062, 1.232) | 7.176 (4.415, 9.829) |
| Wealth Quintile: lower | 0.191 (-0.122, 0.498) | 1.065 (-0.260, 2.448) |
| Wealth Quintile: middle | -0.035 (-0.339, 0.261) | 0.033 (-1.257, 1.561) |
| Wealth Quintile: higher | -0.169 (-0.469, 0.149) | -0.499 (-1.855, 0.974) |
| Wealth Quintile: highest | -0.648 (-0.963, -0.325) | -2.377 (-3.828, -0.913) |
| Education Level: primary | 0.908 (0.335, 1.471) | 4.173 (1.590, 6.321) |
| Education Level: vocational | 0.544 (-0.297, 1.396) | 2.494 (-1.056, 5.990) |
| Education Level: secondary | 0.648 (0.056, 1.237) | 2.695 (0.203, 4.849) |
| Education Level: college | 0.330 (-0.306, 0.949) | 1.501 (-1.009, 3.757) |
| Education Level: university | -0.364 (-1.159, 0.397) | -0.739 (-3.402, 1.835) |
| Marital Status: living with man | -0.014 (-0.392, 0.380) | 0.366 (-1.292, 2.310) |
| Marital Status: divorced | -0.249 (-0.583, 0.098) | -0.967 (-2.364, 0.630) |
| Marital Status: widow | -0.632 (-1.190, -0.010 ) | -2.751 (-4.988, 0.178) |
| Marital Status: not married | -1.137 (-1.395, -0.873) | -4. 305 (-5.308, -3.152) |
| Birth events | -0.115 (-0.167, -0.059) | -0.471 (-0.697, -0.214) |

$q$ Denotes the quantile, Bayesian Credible Intervals are in brackets

Table 4 shows the Bayesian parameter estimates with respective BCI's for the upper quantiles. Again, highest wealth quintile, primary level of education, secondary level of education, marital status: not married were found to be relevant in explaining the uptake of injectable contraceptives in all the upper quantiles estimated while marital status: widow was only relevant at quantile 0.75.

***Table 5.*** *Potential Scale Reduction Factors (PSRF) for all parameters in all estimated quantiles.*

| **Parameters** | ***q* =0.10** | ***q* =0.25** | ***q* =0.50** | ***q* =0.75** | ***q* =0.95** |
|---|---|---|---|---|---|
| Intercept | 1.02 | 1.00 | 1.00 | 1.00 | 1.01 |
| Wealth Quintile: lower | 1.00 | 1.00 | 1.00 | 1.00 | 1.01 |
| Wealth Quintile: middle | 1.00 | 1.00 | 1.00 | 1.00 | 1.02 |
| Wealth Quintile: higher | 1.01 | 1.00 | 1.00 | 1.00 | 1.01 |
| Wealth Quintile: highest | 1.05 | 1.00 | 1.00 | 1.00 | 1.01 |
| Education Level: primary | 1.00 | 1.00 | 1.01 | 1.00 | 1.02 |
| Education Level: vocational | 1.00 | 1.01 | 1.00 | 1.00 | 1.01 |
| Education Level: secondary | 1.01 | 1.00 | 1.00 | 1.00 | 1.00 |
| Education Level: college | 1.02 | 1.00 | 1.00 | 1.01 | 1.01 |
| Education Level: university | 1.00 | 1.00 | 1.00 | 1.00 | 1.01 |
| Marital Status: living with man | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Marital Status: divorced | 1.00 | 1.01 | 1.00 | 1.00 | 1.01 |
| Marital Status: widow | 1.01 | 1.01 | 1.00 | 1.00 | 1.00 |
| Marital Status: not married | 1.01 | 1.00 | 1.00 | 1.00 | 1.00 |
| Birth events | 1.01 | 1.00 | 1.00 | 1.00 | 1.00 |

*q* Denotes the quantile

Table 5, shows the estimated potential scale reduction factors (PSRF) for all the covariates. These were obtained by running two MCMC Gibbs sampling algorithms each of 27000 iterations with an initial burn in of 2000 iterations. It is very vivid from table 5 that convergence have been achieved since all the estimated PSRF's are less than 1.1 which paves way for making reliable inferences.

# 4. Discussions

This study has clearly exhibited that the number of birth events, woman's education level, the status of marriage of the woman and wealth level of woman are the factors that greatly influences the preference of injectable contraceptives to other methods of contraception. Concerning the wealth quintile where a woman belongs, highest wealth category was found to be having negative significant coefficients in all the quantiles of usage of contraceptives (injectable). This implies that reproductive aged-women belonging to the highest category of wealth prefer using other methods of contraception rather than the injectable contraceptives as compared to women in reference category (lowest quintile). In all estimated quantiles, this contradicts study by Johnson [16] and another by Gelata [17] which found that wealthy women tend to utilize modern contraceptives compared to the poor [17]. The negative significance of this variable at all quantiles is a clear proof that this variable truly affects injectable contraceptive uptake in negative way. The effect of the highest wealth quintile becomes strong in the two extreme quantiles (quantile 0.1 and 0.95) which implies that the effect is stronger for women with both high and low probability of using injectable contraceptives, which is usually not shown in ordinary logistic regression.

For education level, primary education and secondary education presented positive significant coefficients in all estimated quantiles showing the positive influence of these variables on the utilization of injectable contraceptives. This means that the reproductive aged women who have attained both primary and secondary education tend to use injectable contraceptives more than women in reference category (no education) in all estimated quantiles which also agrees with a study by Medhanyie [18]. The effect of these variables again on injectable contraceptive uptake is stronger in the two extreme quantiles (0.1 and 0.95) suggesting that the effect is stronger for child bearing women with both low and high propensity of using injectable contraceptives. This may be because women with no education might perceive using injectable contraceptives may have negative side effects.

For marital status, the coefficient of women who are divorced proved to be negatively significant on the uptake of injectable contraceptives in only lower quantiles, this means that the divorced reproductive aged women tend to use other methods of contraception as compared to women in reference category (married) when the probability of using injectable contraceptives is low. Also coefficients for women who are not married were significant at all estimated quantiles implying that there is less uptake of injectable contraceptives for not married child bearing women than the married women. This conforms to reality because if a woman is not married, there is no need to use contraceptives. At the estimated quantiles from 0.1 to 0.75, coefficients of women who are widows are negatively significant meaning that the negative effect of this variable is stronger for women with low probability of using injectable contraceptives.

In all the estimated quantiles, birth events also had negative significance at 95% BCI with increase from quantile 0.1 to the central quantile and a decline in the two estimated upper quantiles. Therefore use of injectable contraceptives reduces with increase in birth events. The effects is more pronounced in the lower and upper extreme quantiles which suggests that for women with both low and high probability of using injectable contraceptives, every additional birth event leads to more use of other methods of contraception as opposed to injectable contraceptives. In Kenya, Kirui et al [13] also found that, use if injectable contraceptives decreases with increase in the number of births.

# 5. Conclusion

The main focus of this study was to model injectable contraceptive uptake using Bayesian binary quantile regression. This was achieved by fitting Bayesian binary quantile regression model at five different quantiles where convergence diagnostics were tested and found to be reasonably robust in all estimated quantiles. The uptake of injectable contraceptives among child bearing women were found to be negatively influenced by wealth quintile: highest, marital status: divorced, widow and never married, and birth events. Injectable contraceptive uptake was also positively influenced by primary and secondary education levels. These predictors have strong effects on the extreme lower quantile (0.1) and extreme upper quantile (0.95). All these effects cannot be seen in ordinary logistic regression. Therefore, marital status, birth events, education level and wealth quintile are significant predictors of injectable contraceptive uptake in Kenya.

This research recommends that the health ministry should strengthen awareness and ensure equal access about injectable contraceptives to child bearing women who have not attained any form of education, those who are never married, those who are divorced, those who are widowed and those with many birth events. Also there is a need to inform women in the highest wealth quintile about importance of injectable contraceptives. Also based in the fact this research utilized cross sectional data, future studies should consider using the Panel Bayesian Binary Quantile Regression (PBBQR) in modelling the uptake of injectable contraceptives.

# Acknowledgements

I thank the Performance Monitoring for Action (PMA) for providing data. I thank my parents for their firm support in my studies despite financial distress. I thank my supervisors Dr. Anthony Wanjoya and Dr. Joel Chelule for their continuous guidance, may God bless you all!

# References

[1] Gonsalves, L., Wyss, K., Cresswell, J. A., Waithaka, M., Gichangi, P., & Hilber, A. M. (2020). Mixed-methods study on pharmacies as contraception providers to Kenyan young people: who uses them and why. *BMJ open, 10 (7), e034769.*

[2] Tilahun, S., & Dimbuene, J. A.-A. Z. T. (2018). Family planning in east Africa: Trends and dynamics. *BMC women's health*.

[3] Mochache, V., Lakhani, A., El-Busaidy, H., Timmerman, M., & Gichangi P. (2018). Pattern and determinants of contraceptive usage among women of reproductive age from digo community residing in kwale, Kenya: results from a cross sectional household survey. *BMC Women's Health, 18 (1), 1-11.*

[4] Akoth, C., Oguta, J. O., Gatimu, S. M. (2021). Prevalence and factors associated with covert contraceptive use in Kenya: a cross sectional study. *BMC Women's Health*. (2021) 21: 1316. Doi: 10.1186/s12889-021-11375-7.

[5] Koenker, R., & Bassett Jr, G. (1978). Goodness of fit and related inferences processes for quantile regression. *Journal of American statistical association, 94 (448), 1296-1310.*

[6] Koenker, R., (2005). Quantile regression[m]. *Econometrics Society Monographs, Cambridge University Press, 33-50.*

[7] Benoit, D. F., & Van den Poel. (2012). Binary quantile regression: a bayesian approach based on asymmetric laplace distribution. *Journal of Applied Econometrics, 27 (7),* 1174-1188.

[8] Mollica, C., & Petrella, L. (2017). Bayesian binary quantile regression for the analysis of bachelor-to-master transition. *Journal of Applied Statistics, 44 (15), 2791-2812.*

[9] Xu, X., Luo, X., Xiao, D., & Wong, S. (2021). Comparative analysis of Bayesian quantile regression models for pedestrian injury severity at signalized intersections. *Journal of Transportation Safety & Security 13 (9), 978-999.*

[10] Kuhudzai, A. G., Van Hal, G., Van Dongen, S., & Hoque, M. (2022). Modelling of south African hypertension: Comparative analysis of the classical and Bayesian quantile regression approaches. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing, 59,* 00469580221082356.

[11] Tigabu, S., Demelew, T., Seid, A., Sime, B., & Manyazewa, T. (2018). Socio economic and religious differentials in contraceptive uptake in western Ethiopia: a mixed-methods phenomenological study. *BMC Women's Health, 18* (1), 1-10.

[12] Beson, P., Appiah, R., & Adomah-Afari, A. (2018). Modern contraceptive use among reproductive-aged women in Ghana: prevalence, predictors and policy implications. *BMC Women's Health, 18 (1), 1-8.*

[13] Kirui, E. K., Mung'atu, J. K., Gichangi, P., Onguto, N. O., & Kamondo, D. K. (2021). Multiple logistic regression model for determinants of injectable contraceptive uptake among women of reproductive age in Kenya. *Journal of Family & Reproductive Health, 15 (2), 82.*

[14] Benoit, D. F., & Van den Poel. (2017). Bayesqr. A Bayesian approach to quantile regression. *Journal of Statistical Software, 76, 1-32.* doi: 10.11648/J.AJPA.20221001.12.

[15] Du, H., Z., Jiang, G., & Huang, S. (2022). The Performances of gelman-rubin and gewege's convergence diagnostics of monte carlo markov chains in Bayesian analysis. *Journal of Behavioral Data Science, 2 (2), 47-72.*

[16] Johnson, O. E. (2017). Determinants of modern contraceptive uptake among Nigerian women: evidence from the national demographic and health survey. *African Journal of reproductive health, 21 (3), 89-95.*

[17] Geleta, D., Kebede, A., Bulcha, G., Usman, H., Hajibediru, K., Dubale. (2021). Prevalence and predictors of contraceptive use among women of premenopausal period in Ethiopia: A retrospective cross-sectional data analysis. *Open Access Journal of Contraception, 12, 149.*

[18] Medhanyie, A. A., Desta, A., Alemayehu, M., Gebrehiwot, T. A., Abrha, A., & Godefay, H. (2021). Factors associated with contraceptive use in Tigray, north Ethiopia. *Reproductive health, 14 (1), 1-11.*

[19] Dichandra, D., Fithriani, I., & Nurrohmah, S. (2021). Parameter estimation of Bayesian quantile regression. *AIP Conference Proceedings 2374, 030010;* https://doi.org/10.1063/5.0059103.