

Multinomial Logistic Regression for Modeling Contraceptive Use Among Women of Reproductive Age in Kenya

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Abstract: Contraceptive use is viewed as a safe and affordable way to halt rapid population growth and reduce maternal and infant mortality. Its use in Kenya remains a challenge despite the existence of family planning programmes initiated by the government and other stakeholders aimed at reducing fertility rate and increasing contraceptive use. This study aimed at modeling contraceptive use in Kenya among women of reproductive age using Multinomial logistic regression technique. A household based cross-sectional study was conducted between November 2008 and March 2009 by Kenya National Bureau of Statistics on women of reproductive age to determine the country's Contraceptive Prevalence Rate and Total Fertility Rate among other indicators, whose results informed my data source. Multinomial logistic regression analysis was done in R version 3.2.1. statistical package. Modern method was the most preferred contraceptive method, of which Injectable, female sterilization and pills were the common types. Descriptive Analysis showed richest women aged between 30-34 years used modern contraceptives, while poorer women aged 35-39 years preferred traditional method. Multinomial Logistic Regression Analysis found marital status, Wealth category, Education level, place of Residence and the number of children a woman had as significant factors while age, religion and access to a health facility were insignificant. Simulation study showed that MLR parameters estimates converged to their true values while their standard errors reduced as sample size increased. Kolmogorov-Smirnov statistic of the MLR parameter estimates decreased while the P-value increased as the sample size increased and remained statistically insignificant. Marital status, Wealth category, Education level, place of Residence and the number of children a woman had could determine the contraceptive method a woman would choose, while age, religion and access to a health facility had no influence on the decision of choosing folkloric, traditional or modern method of contraception. MLR parameter estimates are consistent and normally distributed.

Keywords: Contraceptive Method, Reproductive Age, Multinomial Logistic Regression (MLR), Consistent, Normally Distributed

1. Introduction and Literature Review

1.1. Background of the Study

The desire to have spaced and limited births by individuals is the basis for the use of Contraceptive. The use of Contraceptive is the most effective method of reducing unintended pregnancies and abortions, and its use has greatly improved maternal, infant and child health and survival.

“Effective contraception is healthy and socially beneficial to mothers and their children and households [1]”. According to an article done in 2000 by Grimes, 600,000 women die globally every year from pregnancy-related causes, of which 75,000 cases are due to unsafe abortions. Failure or lack of contraceptive services is the cause of about 200,000 of these maternal deaths. “Mothers who have unintended births tend to suffer postpartum depression, feelings of powerlessness, increased time pressure and a general physical health

deterioration. They also have poor quality relationships with their children, as they spend less leisure time with them [2]”.

1.2. Review of Previous Studies on the Subject of Study

Ojakaa carried out a study on the Patterns and Determinants of Fertility Transition in Kenya. The study used Multivariate analysis to determine the significance of various factors affecting contraceptive use. Analysis showed that motivation for fertility control and proximity to family planning services were significant factors in determining the contraceptive prevalence. The latter was explained by high exposure to family planning messages reported by women who accessed family planning services at the health facilities. However, access to family planning services was not in any way affecting uptake of contraceptive [3].

Mohammed's study on Determinants of modern contraceptive utilization among married women of reproductive age group in North Shoa Zone, Amhara Region, Ethiopia, revealed that use of modern contraceptive among women who were currently married was 46.9%. Among the different methods of contraceptives used, Injectable contraceptives were found to be the most preferred, while intrauterine device (16.8%) was the second, followed by pills and norplant at 14% and 4.3% respectively. A multiple logistic regression analysis revealed that the desire to have more children; couples discussion about family planning issues; and husbands decision on contraceptive method to be used, determined the type of contraceptive to be used on odds-ratio of 9.27, 7.32 and 2.82 respectively, considering a 95% confidence interval. Monthly income and the number of children alive were notably associated with the use of modern methods of contraceptive [4].

In their study on Correlates of Contraceptive use among Ghanaian women of Reproductive Age (15-49 Years), Amponsah *et. al.* used logistic and multinomial logistic regression methods. The analysis showed that wealth status, level of education, ownership of health insurance, number of surviving children, marital status, location and geographical area of residence, religion and women autonomy, significantly correlated with the contraceptive use among women in Ghana. Further, the study showed that women who took health decisions jointly with their partners were more likely to use modern contraceptives as compared to women who take health decisions alone [5].

Research by Kidayi, on the Determinants of Modern Contraceptive Use among Women of Reproductive Age in Tanzania: Evidence from Tanzania Demographic and Health Survey Data, multinomial logistic regression was used to determine the predictors of modern contraceptive use. Among the predictors studied, Women empowerment, male-female age difference and the desire to have children were found to be significant predictors of modern contraceptive usage. However, women sexual violence as a factor was not associated with modern contraceptive use. The conclusion drawn from this study emphasized the need to promote contraceptive use among women of reproductive age of low and middle income countries, especially after concurring

with the previous studies [6].

Ettarh and Kyobutungi sought to determine the spatial variation in modern contraceptive use and unmet need for family planning in Kenya. The study also sought to establish whether the variations in contraceptive use were affected by inequalities in physical access to health facilities. Survey findings of 2008-2009 Kenya Demographic and Health Survey were used for the analysis. Multivariate logistic regression was explored to determine whether the influence of distance to the nearest health facility and health facility density, among other covariates influenced modern contraceptive use and unmet need. The study found that modern contraceptive use was significantly less among women who resided more than 5 Km away from a health facility as compared to those nearest (5 Km or less). Moreover, women from counties with higher health facility density were found to be 53% more likely to use modern contraceptives compared to those who live in counties with low health facility density. In Contrast, the analysis showed that distance and health facility density in the county were not significantly associated with unmet need for contraceptives [7].

1.3. Statement of the Problem

Past studies on contraceptive use in Kenya have used binary and multiple logistic regression methods to determine the significance of factors which predict uptake and non-use of contraceptives by women. Since not all contraceptives are appropriate in all situations, to predict the probability of more than two different possible contraceptive methods, binary logit models cannot be used rather Multinomial Logistic Regression (MLR) model. Complexity in interpreting MLR analysis is the reason behind little research on this model.

1.4. Justification

The Government needs to know what factors may make a woman to prefer a certain contraceptive over the other. This ought to be achieved with minimum cost and high precision. The model developed from this study will help policymakers to predict the contraceptive method used by different women, reasons behind using the method and provide safe family planning methods to curb population pressure. The study will also enrich existing literature on MLR application.

1.5. Objectives

General

The main objective is to model contraceptive use among women in Kenya using multinomial logit.

Specific

1. To derive MLR parameter estimates using Maximum Likelihood Estimation method.
2. To determine the asymptotic properties of the derived MLR parameter estimates.
3. To model contraceptive use among women in Kenya using multinomial logit.

2. Methodology

2.1. Introduction

This chapter highlights an overview of the multinomial logistic regression model, how the model parameter estimates were obtained, and the asymptotic properties of the parameter estimates as well as the derived fitted models.

2.2. Multinomial Logistic Regression Model

Multinomial logistic regression implies that a multivariate rather than a univariate Generalized Linear Model (GLM) has to be used to analyze data with three or more unordered response categories. This is popular in marketing and related fields where the categories frequently represent different products or outcomes.

Let $\pi_{ij} = \text{pr}(y = ij)$ for a fixed set of explanatory variables, with $\sum_{ij} \pi_{ij} = 1$. For observations at that set, we treat the counts at the J categories of y as multinomial with probabilities $\pi_{i1}, \pi_{i2}, \dots, \pi_{ij}$. Logit models pair each response category with a baseline category, where the baseline category will be the first response category for this study.

The general multinomial logistic regression model is;

$$\text{logit}(\pi_{ij}) = \sum_{k=0}^K x_{ik} \beta_{kj}, i = 1, 2, 3, \dots, N; j = 2, 3, 4, \dots, J; x_{i0} = 1 \quad (1)$$

The log odds became

$$\log\left(\frac{\pi_{ij}}{\pi_{i1}}\right) = \sum_{k=0}^K x_{ik} \beta_{kj} \quad (2)$$

Back-transforming equation (2) above, the response probability for the j^{th} category is obtained as

$$\pi_{ij} = \frac{\exp(\sum_{k=0}^K x_{ik} \beta_{kj})}{1 + \sum_{j=2}^J \exp(\sum_{k=0}^K x_{ik} \beta_{kj})} \quad (3)$$

and for the baseline category as

$$\pi_{i1} = \frac{1}{1 + \sum_{j=2}^J \exp(\sum_{k=0}^K x_{ik} \beta_{kj})} \quad (4)$$

Where $\beta_{i1} = 0$

2.3. Derivation of Model Parameter Estimates

In order to obtain the model parameter estimates, let y_{ij} denote the j^{th} response outcome associated with the i^{th} explanatory variable for $j = 2, 3, \dots, J$; $i = 1, 2, \dots, N$ and x_{ik} ; the value of the k^{th} explanatory variables for subject i , which follows a multinomial distribution whose Probability Mass Function (PMF) is of the form;

$$f(y/\beta) = \frac{n_i!}{\prod_{j=1}^J y_{ij}!} \prod_{j=1}^J \pi_{ij}^{y_{ij}} \quad (5)$$

Let $(\beta_{0j}, \beta_{1j}, \beta_{2j}, \dots, \beta_{Kj})$ denote parameters for the j^{th} logit. The maximum likelihood estimator is obtained by maximizing equation (5) above with respect to β .

$$L(\beta/y) = \prod_{i=1}^N [f(y/\beta)] \quad (6)$$

where N is the total number of observations.

All the factorial terms are treated as constants as they do not contain the term π_{ij} . In which the likelihood equation after grouping like-terms together becomes;

$$L(\beta/y) = \prod_{i=1}^N \prod_{j=2}^J \left(\frac{\pi_{ij}}{\pi_{i1}}\right)^{y_{ij}} \pi_{i1}^{n_i} \quad (7)$$

Replacing the terms $\frac{\pi_{ij}}{\pi_{i1}}$ and π_{ij} in equation (7) above with equations (2) and (4), equation (7) can be rewritten as;

$$L(\beta/y) = \prod_{i=1}^N \prod_{j=2}^J \exp(\sum_{k=0}^K x_{ik} \beta_{kj})^{y_{ij}} \left[\frac{1}{1 + \sum_{j=2}^J \exp(\sum_{k=0}^K x_{ik} \beta_{kj})} \right]^{n_i} \quad (8)$$

Taking the natural log of the above equation we obtain the log likelihood function;

$$l(\beta) = \sum_{i=1}^N \sum_{j=2}^J (y_{ij} \sum_{k=0}^K x_{ik} \beta_{kj}) - n_i \log\{1 + \sum_{j=2}^J \exp(\sum_{k=0}^K x_{ik} \beta_{kj})\} \quad (9)$$

To get the values of the MLE of β , Newton-Raphson (NR) method is used to compute the first and second derivatives of the above log likelihood function [8]. The first derivative is derived as;

$$\frac{\partial(l(\beta))}{\partial \beta_{kj}} = \sum_{i=1}^N x_{ik} (y_{ij} - n_i \pi_{ij}) \quad (10)$$

And the second derivative as;

$$\frac{\partial^2(l(\beta))}{\partial \beta_{kj}^2} = - \sum_{i=1}^N n_i x_{ik} \pi_{ij} (1 - \pi_{ij}) x_{ik}'; j' = j \quad (11)$$

Whereby the two derivatives can be expressed in matrix form as;

$$\frac{\partial(l(\beta))}{\partial \beta_{kj}} = X^T (y - \eta) \quad (12)$$

And

$$\frac{\partial^2(l(\beta))}{\partial \beta_{kj}^2} = -X^T W X \quad (13)$$

Where W is a diagonal matrix of weights whose dimension is $n \times n$ and the diagonal elements are $n_i \pi_{ij} (1 - \pi_{ij})$ and 0's elsewhere. X is a $n \times p$ matrix of observations whose transpose is X^T and $X^T W X$ is the hessian matrix of $p \times p$, $\eta = n_i \pi_{ij}$ and $(y - \eta)$ is a vector matrix of $p \times 1$.

The current estimate $\hat{\beta}^{(t-1)}$ is updated each time iteration is done using the equation;

$$\hat{\beta}^{(t)} = \hat{\beta}^{(t-1)} + \left[- \frac{\partial^2(l(\hat{\beta}^{(t-1)}))}{\partial \beta_{kj}^2} \right]^{-1} \frac{\partial(l(\hat{\beta}^{(t-1)}))}{\partial \beta_{kj}} \quad (14)$$

$$= \hat{\beta}^{(t-1)} + [X^T W X]^{-1} X^T (y - \eta) \quad (15)$$

Which upon convergence, $\hat{\beta}^{(t)} \cong \hat{\beta}^{(t-1)}$ the equation can be rearranged by the Iteratively Reweighted Least Squares (IRWLS) algorithm as;

$$\hat{\beta} = [X^T W X]^{-1} X^T W Y \quad (16)$$

Which is the Maximum Likelihood Estimator of the

parameter β and $[X^T W X]^{-1}$ is the estimated covariance matrix of $\hat{\beta}$ [9, 10].

2.4. Asymptotic Properties of the MLE $\hat{\beta}$

The asymptotic properties studies what happens to estimators as N increases with the number of predictor variables being fixed. This is important because models estimated using large samples of data generate asymptotic results which provide useful approximation of the model estimators' behaviour and their test statistics.

2.4.1. Asymptotic Consistency of $\hat{\beta}$

If $\hat{\beta}_N$ is a consistent estimator of β on sample N , $\text{pr}(|\hat{\beta}_N - \beta| > \varepsilon) \rightarrow 0$ as $N \rightarrow \infty$ for arbitrary constant $\varepsilon > 0$, denoted as $\text{plim}(\hat{\beta}_N) = \beta$.

By convention, equation (15) can be written as

$$\hat{\beta} = \beta + [X^T W X]^{-1} X^T W \eta \quad (17)$$

Introducing the term N to the equation we obtain the probability limit as;

$$\text{plim}(\hat{\beta}) = \beta + \left[\frac{X^T W X}{N} \right]^{-1} \text{plim} \left(\frac{X^T W \eta}{N} \right) \quad (18)$$

By the assumptions of Law of Large Numbers (LLN) that;

- (i) $\text{plim} \left[\frac{X^T W X}{N} \right] = Q$, where Q exists and is finite as infinite variance is not measurable.
- (ii) $\left[\frac{X^T W X}{N} \right]$ becomes the mean value of $X^T W X$ and that Q^{-1} exists.
- (iii) $\text{plim}[\eta^T W \eta] = \sigma^2 W$

$$\text{plim}(\hat{\beta}) = \beta \quad (19)$$

Thus $\hat{\beta}$ is a consistent estimator of β .

2.4.2. Asymptotic Normality of $\hat{\beta}$

To obtain the asymptotic distribution of the estimator, equation (17) is multiplied through by \sqrt{N} to obtain a non-zero yet finite asymptotic variance [11] as

$$\sqrt{N}(\hat{\beta} - \beta) = \left[\frac{X^T W X}{N} \right]^{-1} \left[\frac{X^T W \eta}{\sqrt{N}} \right] \quad (20)$$

The probability limit variance of $\sqrt{N}(\hat{\beta} - \beta)$ becomes;

$$\begin{aligned} & \text{plim}[\sqrt{N}(\hat{\beta} - \beta)][\sqrt{N}(\hat{\beta} - \beta)]^T \\ &= \text{plim} \left\{ \left[\frac{X^T W X}{N} \right]^{-1} \left[\frac{X^T W \eta}{\sqrt{N}} \right] \left[\frac{X^T W \eta}{\sqrt{N}} \right]^T \left[\frac{X^T W X}{N} \right]^{-1} \right\} \quad (21) \end{aligned}$$

$$= \text{plim} \left\{ \left[\frac{X^T W X}{N} \right]^{-1} \left[\frac{X^T W \eta \eta^T W X}{N} \right] \left[\frac{X^T W X}{N} \right]^{-1} \right\} \quad (22)$$

By assumption (i), (ii) and (iv), the above equation becomes

$$\text{plim}[\sqrt{N}(\hat{\beta} - \beta)][\sqrt{N}(\hat{\beta} - \beta)]^T = Q^{-1} Q \sigma^2 W Q^{-1} \quad (23)$$

which is the limit distribution of the maximum likelihood

estimator $\hat{\beta}$ according to Gauss-Markov assumptions, [12] written as

$$\sqrt{N}(\hat{\beta} - \beta) \xrightarrow{d} N[0, \sigma^2 W Q^{-1}] \quad (24)$$

and the asymptotic distribution as

$$\hat{\beta} \xrightarrow{a} N[\beta, \sigma^2 W N^{-1} Q^{-1}] \quad (25)$$

This implies that $\hat{\beta}$ has an asymptotic multivariate normal distribution.

2.5. Estimation of Response Probabilities

The estimation of the response probabilities by the parameter estimates of the fitted model will be;

$$\hat{\pi}_{ij} = \frac{\exp(\sum_{k=0}^K x_{ik} \hat{\beta}_{kj})}{1 + \sum_{j=1}^J \exp(\sum_{k=0}^K x_{ik} \hat{\beta}_{kj})} \quad (26)$$

which is the estimation of the response probabilities $j = 2, 3, \dots, J$ and the denominator ensures the sum of probabilities $\sum_{j=1}^J \pi_{ij} = 1$. For the baseline response probability $j=1$, $\beta_{i1} = 0$ which is an identification constraint and the probability is;

$$\hat{\pi}_{i1} = \frac{1}{1 + \sum_{j=2}^J \exp(\sum_{k=0}^K x_{ik} \hat{\beta}_{kj})} \quad (27)$$

2.6. Statistical Significance Tests

Test of statistical significance determines the probability of association between variables in a study and how strong the association is.

The null hypothesis was $H_0: \hat{\beta}_{kj} = 0$ testing whether x_{ik} is significant or not.

The test statistic used to test for significance of the parameter estimates was;

$$t_k = \frac{\hat{\beta}_k - \beta_k}{\sqrt{\text{var}(\hat{\beta}_k)}} = \frac{\hat{\beta}_k}{\sqrt{\text{var}(\hat{\beta}_k)}} \sim t_{(N-K-1), \alpha} \quad (28)$$

with N being the sample size and K as the number of independent variables.

The criterion being to reject H_0 if;

$$t_k > t_{(N-K-1), \alpha} \text{ or } p_{\text{value}} < \alpha$$

at the desired significance level [13].

3. Data Analysis

3.1. Introduction

This chapter highlights the data source of the study, sample size used, data variables and the results of the study.

3.2. Data Source

The study used secondary data derived from the results of Kenya Demographic and Health Survey conducted between November 2008 and March 2009 by Kenya National Bureau

of Statistics on women of reproductive age to determine the country's Contraceptive Prevalence Rate and Total Fertility Rate among other indicators.

3.3. Study Design

A sample size of 8,220 women between 15 - 49 years of age was used.

3.4. Sample Inclusion and Exclusion Criteria

Women included in this study were Kenyan women aged 15 years and above but not more than 49 years of age.

This was referred to as reproductive age in this study.

3.5. Data Variables

i). Response Variable

Contraceptive method: A polytomous outcome with three responses: Traditional method, Modern method and Folkloric method.

Traditional methods defined in this study were periodic abstinence and withdrawal methods; Modern methods were Pills, Intra Uterine Device (IUD), Injections, Diaphragm, Condom, female sterilization, male sterilization, Norplant, abstinence, Lactational Amenorrhea and female condom; while Folkloric methods defined in this study were all other family planning methods not defined above.

ii). Predictor Variables

Social economic factors used in this study were education and wealth index, while the social demographic factors were

residence, age, religion, number of children alive, marital status and health facility access.

4. Results and Discussion

4.1. Descriptive Analysis

The most preferred method of contraceptive by women was modern contraceptive with 85.7% of the sampled women reporting to use this method.

Table 1. A Table of Contraceptive method used.

Contraceptive method	Women	Percent
Folkloric method	139	1.7%
Modern method	7191	87.5%
Traditional method	890	10.8%

Injections, female sterilization and pills were the most commonly used modern methods among women and accounted for 44.0%, 16.1% and 13.1% of the total contraceptive uptake, respectively. This shows there is a breakthrough as far as embracing safe contraception is concerned. In the traditional method, women who reported to use periodic abstinence were 9.3% of the total respondents while those who reported to use other (folkloric) methods accounted for 1.7% of the total women sampled.

Table 2. Relation between Age and Contraceptive method used.

Contraceptive method	Age						
	15-19	20-24	25-29	30-34	35-39	40-44	45-49
Folkloric method	1	15	20	15	35	32	21
Modern method	70	604	1,202	1,648	1,440	1,266	961
Traditional method	4	77	116	159	215	130	189

Test on the hypothesis that;

H_0 : Contraceptive method used is independent of a woman's age

H_1 : Contraceptive method used is not independent of a woman's age at 5% significance level.

Pearson's Chi-squared Test of independence

X-squared = 76.948, df = 12, p-value = 0.0001

Pearson's Chi-square independence test statistic was highly significant and the null hypothesis was rejected. Contraceptive method was therefore dependent on a woman's age. The highest number of women who reported to use the modern contraceptive method was between the age of 30 and 34, while majority of those who reported to use either the traditional or folkloric were of 35 to 39 years of age. A general observation from the analysis was that, in the three contraceptive methods, contraceptive use seemed to increase as age increases. This trend is common among women where one starts using contraceptive at a certain age, probably after getting her ideal family.

Table 3. Relation between Wealth Index and Contraceptive method used.

Contraceptive method	Wealth Index				
	Middle	Poorer	Poorest	Richer	Richest
Folkloric method	25	50	17	19	28
Modern method	1,652	1,276	785	1,728	1,750
Traditional method	215	182	103	203	187

Test on the hypothesis that;

H_0 : Contraceptive method used is independent of a woman's Wealth level vs

H_1 : Contraceptive method used is not independent of a woman's Wealth level at 5% significance level.

Pearson's Chi-squared Test of independence

X-squared = 40.662, df = 8, p-value = 0.0002

Pearson's Chi-square independence test statistic was highly significant and the null hypothesis was rejected. Contraceptive method was therefore dependent on a woman's Wealth level. Fifty (36.0%) out of 139 women who reported to use folkloric method were in the poorer quintile category, while 215 of those who reported to use traditional method were in the middle quintile category as shown in Table 3. Moreover, women in the poorer wealth level were less likely to use traditional or modern contraceptive methods as compared to those in the middle class due to the

unaffordability of the modern contraceptives. This could have prompted women in the poorer wealth category to use other cheaper and unsafe contraceptive methods. Approximately half of the total women reported to use modern contraceptives were in the richer and the richest quintile categories and jointly accounted for 42.3% of the total women who reported to use any contraceptive. This shows there is need for the Government and the concerned stakeholders to provide modern contraceptive services at subsidized prices especially to those who can't afford them.

Table 4. Relation between Number of Living children and Contraceptive method used.

Contraceptive method	Number of Children															
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Folkloric method	6	8	16	9	24	21	38	8	0	9	0	0	0	0	0	0
Modern method	13	417	1,109	1,481	1,344	991	776	537	264	114	73	35	37	0	0	0
Traditional method	1	50	105	105	196	133	122	81	37	11	10	11	0	13	0	15

Test on the hypothesis that;

H_0 : Contraceptive method used is independent of a woman's number of children

H_1 : Contraceptive method used is not independent of a woman's number of children at 5% significance level.

Pearson's Chi-squared Test of independence

X-squared = 467.95, df = 28, p-value = 0.0001

Pearson's Chi-square independence test statistic was highly significant and the null hypothesis was rejected. Contraceptive method was therefore dependent on the number of children a woman has. Women with few or no children were less likely to use contraceptives compared to those who have more children as highlighted in Table 4. This could be due to the fact that women without children avoid the use of contraceptives as they desire to have children compared to those who already have children. However, if a woman bears seven or more children, chances of using contraceptives diminishes with increase in the number of children. Women who reported to use modern contraceptives had few children as compared to those who reported to use traditional and folkloric methods, where those who reported to use folkloric had the highest number of children as illustrated. This trend shows the effectiveness of the three contraceptive methods, with the modern being the most effective and folkloric the least effective. Modern methods therefore guarantee the most effective family planning and its use should be upheld while the other methods be discouraged.

4.2. Multinomial Regression Analysis

4.2.1. Significance of the Predictor Variables

At 5% level of significance, the study found there was association between the particular contraceptive method a woman chose and her socio-economic factors. Among the socio-economic factors, a woman's wealth quintile level and education level were found to be significant in determining whether she will choose folkloric, traditional or modern method of contraception. However, mixed correlation existed between the contraceptive method a woman chose and her socio-demographic factors. Place of residence, marital status and the number of children a woman had, informed a woman's choice of contraceptive.

Despite age, religion and access to a health facility being factors that could determine the likelihood of a woman using contraceptive, at 5% the study found that they were not key factors a woman considered in choosing a particular type of contraceptive method.

4.2.2. Goodness of Fit

A comparison of the model with all predictor variables (Big model) and a model with the significant predictor variables (Small model) was used to form an hypothesis that;

H_0 : The Big model is a good fit for the data.

H_1 : The Big model is not a good fit for the data.

The deviance statistics was computed as;

Deviance (G^2)

Log likelihood of the big model = -3415.193 (df=40)

Log likelihood of the small model = -3420.136 (df=30)

$G^2 = -2$ (Log likelihood of the small model - Log likelihood of the big model)

$G^2 = -2$ ((-3420.136) - (-3415.193)) = 9.887

$p_{value} = 1 - pchisq(G^2, df=10) = 0.4505$

The P-value obtained from the deviance was not statistically significant at 5% level of significance and the study failed to reject the null hypothesis. The conclusion was that the big model is a good fit for the data. Thus the parameter estimates obtained from this model can be used to predict the probability of a woman choosing any of the three contraceptive methods given the predictor variables.

4.3. Fitting the Contraceptive Use Model

The regression coefficients found significant were used to build the multinomial logistic model of using the three contraceptive methods with folkloric method as the baseline response category.

4.3.1. Modern Method Relative to Folkloric Method

The multinomial logistic regression of modern method relative to folkloric method showed that education level a woman attained, place of residence, number of living children she has, marital status and her wealth status determined the use of modern contraceptives with P-value < 0.05. The multinomial logistic regression model to predict the probability of a woman choosing modern method with respect to folkloric method was;

$$\text{Contraceptive method} \sim \text{Marital status} + \text{Wealth Index} + \text{Highest Education level} + \text{Residence}$$

The equivalent log odd of Modern vs. Folkloric was fitted as;

$$\log\left(\frac{\hat{\pi}_{\text{Modern}}}{\hat{\pi}_{\text{Folkloric}}}\right) = -0.695\text{Residence: Urban} \\ -0.796\text{Wealth Index: Poorer} + 0.825\text{Wealth Index: Richer} \\ + 0.994\text{Wealth Index: Richest} \\ + 3.138\text{Marital Status: Living together} \\ + 2.650\text{Marital Status: Married} \\ + 3.771\text{Marital Status: Not Living together} \\ + 3.194\text{Marital Status: Widowed} \\ + 1.478\text{Highest Education level: No education} \\ + 0.791\text{Highest Education level: Primary} \\ + 0.789\text{Highest Education level: Secondary}$$

4.3.2. Interpretation of Log-odds of Modern Method Relative to Folkloric Method

Women who had no education were 1.50 times more likely to use modern contraceptive as compared to folkloric method. Similarly, those who had secondary education had a higher chance of using modern contraceptives as compared to using folkloric method. Women in the poorer quintile category were 0.80 times less likely on odds-scale to use modern contraceptives as opposed to those in the middle quintile category. However, women in the richer and the richest quintile categories were 0.83 times and 0.99 times respectively, more likely to use modern contraceptives relative to those in the middle quintile category. In addition, women who dwelled in the rural areas were 0.70 times more likely to use modern contraceptive as compared to using folkloric method. Women living together with their spouses and the widowed, significantly (P-value<0.000) preferred to use modern contraceptives relative to folkloric methods. Moreover, those not living together with their spouses and those married were 3.77 times and 2.65 times respectively, more probable to use modern contraceptive than those divorced.

4.3.3. Traditional Method Relative to Folkloric Method

The multinomial logistic regression of traditional method relative to folkloric method showed that education level a woman attained, place of residence, number of living children, marital status and her wealth status were associated with the use of traditional contraceptives with P-value < 0.05. The multinomial logistic regression model to predict the probability of a woman choosing traditional method with

respect to folkloric method became;

$$\text{Contraceptivemethod} \sim \text{Maritalstatus} + \text{WealthIndex} \\ + \text{HighestEducationlevel} + \text{Residence} \\ + \text{Living children}$$

The fitted log odds of the traditional vs. folkloric was;

$$\log\left(\frac{\hat{\pi}_{\text{Traditional}}}{\hat{\pi}_{\text{Folkloric}}}\right) = -1.053\text{Residence: Urban} \\ -0.733\text{WealthIndex: Poorer} \\ +0.714\text{WealthIndex: Richer} + 0.985\text{WealthIndex: Richest} \\ + 1.664\text{MaritalStatus: Livingtogether} \\ + 1.055\text{MaritalStatus: Married} \\ + 2.098\text{MaritalStatus: NotLivingtogether} \\ + 0.738\text{HighestEducationlevel: Secondary} \\ + 0.119\text{Living children}$$

4.3.4. Interpretation of Log-odds of Traditional Method Relative to Folkloric Method

Women who had secondary education were 0.74 times more likely to use traditional contraceptives as opposed to folkloric contraceptives. The multinomial logit of a woman using traditional method as compared to folkloric method was significantly higher by 0.71 units and 0.99 units if she was in the richer and richest wealth categories respectively, as compared to one in the middle quintile category. Chances of a woman choosing traditional method were 0.12 times higher as compared to choosing folkloric if she bears more children. Women who dwell in the rural were 1.05 times more likely to use traditional method relative to folkloric method. Married women, those living together and those who don't live together with their spouses, significantly (P-value<0.000) preferred to use traditional contraceptives relative to folkloric methods on multinomial log-odds scale of 1.06, 1.66 and 2.10, respectively.

From the two log-odds equations of modern and traditional methods relative to folkloric method, the estimated probability of choosing either one of the three contraceptive will be;

The likelihood of a woman choosing folkloric method of contraceptive is to be computed as;

$$\frac{1 - \hat{\pi}_{\text{Folkloric}}}{\hat{\pi}_{\text{Folkloric}}} = \exp\{y_1\} + \exp\{y_2\} \\ \hat{\pi}_{\text{Folkloric}} = \frac{1}{1 + \exp\{y_1\} + \exp\{y_2\}} \quad (29)$$

Similarly, the probability of choosing modern method of contraceptive will be;

$$\hat{\pi}_{\text{Modern}} = \hat{\pi}_{\text{Folkloric}} \times \exp\{y_1\} \\ \hat{\pi}_{\text{Modern}} = \frac{\exp\{y_1\}}{1 + \exp\{y_1\} + \exp\{y_2\}} \quad (30)$$

Finally, the chance of a woman going for the traditional methods as a method of contraceptive will be;

$$\hat{\pi}_{\text{Traditional}} = \hat{\pi}_{\text{Folkloric}} \times \exp\{y_2\} \\ \hat{\pi}_{\text{Traditional}} = \frac{\exp\{y_2\}}{1 + \exp\{y_1\} + \exp\{y_2\}} \quad (31)$$

Where $y_1 = \log\left(\frac{\hat{\pi}_{\text{Modern}}}{\hat{\pi}_{\text{Folkloric}}}\right)$ and $y_2 = \log\left(\frac{\hat{\pi}_{\text{Traditional}}}{\hat{\pi}_{\text{Folkloric}}}\right)$

The three equations above will give a criteria based on probability, the three contraceptive method a woman aged between 15 and 49 years is likely to choose.

4.4. Consistency of Multinomial Logistic Regression Parameter Estimates

A simulation study of an increasing random samples of $N=2,000$, $N=4,000$, $N=6,000$ and $N=8,000$ was used to study

the behaviour of multinomial logit parameter estimates and their Simulated Standard errors for each of the sample size. The study used arbitrary fixed values of the parameter estimates obtained from MLR model of Contraceptive Use as true values. Analysis showed that the parameter estimates converged to their true values while the Simulated Standard errors decreased each time the sample size was increased. This shows that maximum likelihood estimators generated by a multinomial regression model are consistent estimators [14].

Table 5. Multinomial Logistic Regression Parameter Estimates and their Simulated Standard Errors at selected Sample Sizes.

True value	Estimator	N=2,000		N=4,000		N=6,000		N=8,000	
		Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
-0.695	$\hat{\beta}_{11}$	-0.697	0.0020	-0.698	0.0014	-0.698	0.0011	-0.696	0.0009
1.478	$\hat{\beta}_{12}$	1.486	0.0027	1.480	0.0019	1.480	0.0015	1.479	0.0013
-0.795	$\hat{\beta}_{13}$	-0.799	0.0020	-0.796	0.0014	-0.797	0.0011	-0.796	0.0010
3.138	$\hat{\beta}_{14}$	3.155	0.0046	3.145	0.0031	3.144	0.0026	3.141	0.0023
-1.053	$\hat{\beta}_{21}$	-1.060	0.0022	-1.056	0.0015	-1.055	0.0012	-1.053	0.0011
0.738	$\hat{\beta}_{22}$	0.742	0.0027	0.737	0.0020	0.739	0.0015	0.738	0.0013
-0.733	$\hat{\beta}_{23}$	-0.739	0.0021	-0.735	0.0015	-0.734	0.0012	-0.734	0.0011
1.644	$\hat{\beta}_{24}$	1.673	0.0043	1.669	0.0030	1.670	0.0025	1.666	0.0022

SE is the Simulated Standard Error

4.5. Normality of Multinomial Logistic Regression Parameter Estimates

4.5.1. Kolmogorov-Smirnov Test of Normality

To determine the normality of Multinomial Logistic Regression (MLR) parameter estimates, Kolmogorov-Smirnov normality test was used and results tabulated in Table 6.

Table 6. Kolmogorov-Smirnov test of Normality on Parameter Estimates at selected sample sizes.

Estimator	N=2,000		N=4,000		N=6,000		N=8,000	
	KS	Pvalue	KS	Pvalue	KS	Pvalue	KS	Pvalue
$\hat{\beta}_{11}$	0.0335	0.1618	0.0195	0.9186	0.0159	0.9623	0.0126	0.9975
$\hat{\beta}_{12}$	0.0156	0.4619	0.0270	0.7089	0.0222	0.9105	0.0178	0.9688
$\hat{\beta}_{13}$	0.0233	0.6508	0.0215	0.7699	0.0173	0.9118	0.0158	0.9650
$\hat{\beta}_{14}$	0.0251	0.5551	0.0201	0.8130	0.0205	0.7928	0.0160	0.9599
$\hat{\beta}_{21}$	0.0190	0.6256	0.0271	0.4425	0.0227	0.6808	0.0214	0.7061
$\hat{\beta}_{22}$	0.0291	0.3668	0.0181	0.9004	0.0146	0.9697	0.0119	0.9835
$\hat{\beta}_{23}$	0.0184	0.8913	0.0246	0.5806	0.0193	0.8487	0.0178	0.9098
$\hat{\beta}_{24}$	0.0201	0.8134	0.0191	0.8584	0.0173	0.9261	0.0138	0.9631

KS is the Kolmogorov-Smirnov Statistic

The hypothesis to be tested was formulated as;

H_0 : Multinomial Logistic Regression parameter estimates are normal vs

H_1 : Multinomial Logistic Regression parameter estimates are not normal at 5% significance level.

There was no enough evidence to reject the null hypothesis as the Kolmogorov-Smirnov Statistic was insignificant at 5% for all the parameter estimates. The Simulated Multinomial Logistic Regression parameter estimates were therefore normally distributed. Further, as the sample size increased, the Kolmogorov-Smirnov Statistic value decreased while the P-value increased but remained relatively insignificant.

4.5.2. Quantile Normal Graph Plot

A qq-plot to study the behaviour of the MLR parameter estimates from the simulation study at different sample sizes shows the simulated parameter estimates aligned themselves in a straight line, indicating that the MLR parameter estimates have a normal distribution.

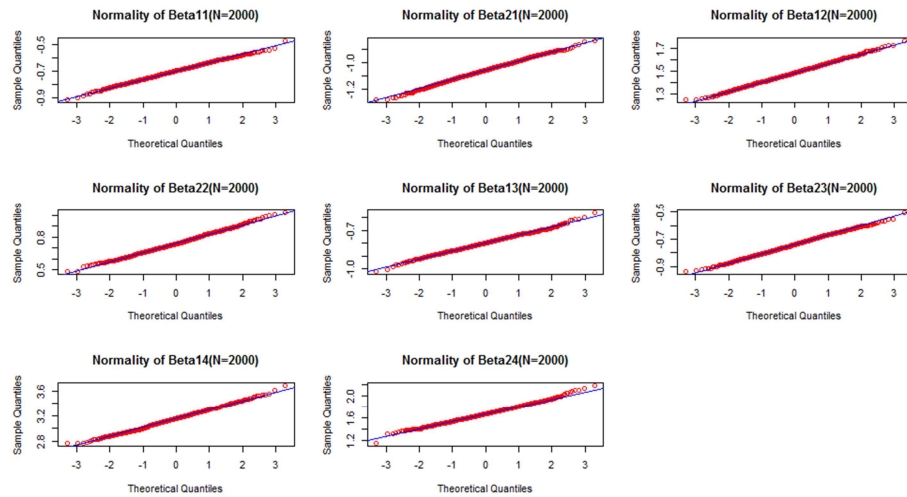


Figure 1. Normality qq-plot of Multinomial Logistic Regression Parameter Estimates when $N=2,000$.

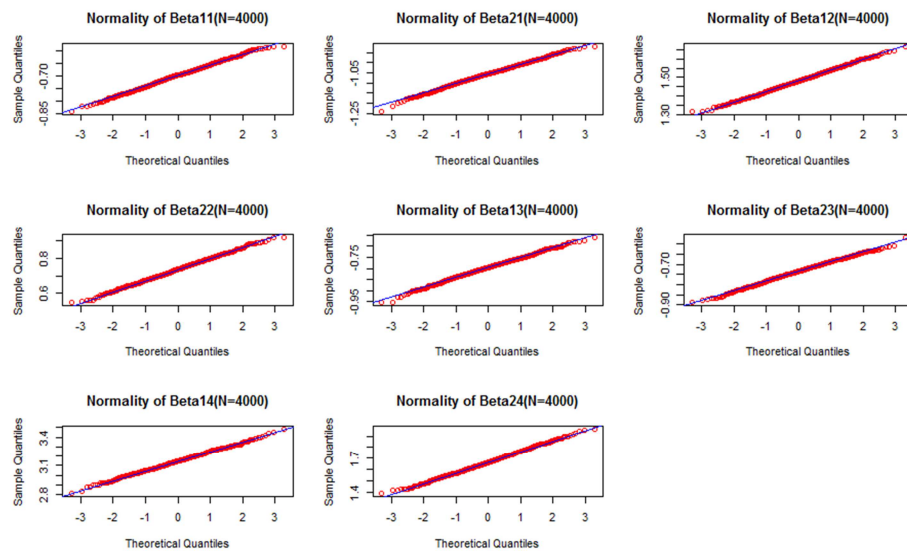


Figure 2. Normality qq-plot of Multinomial Logistic Regression Parameter Estimates when $N=4,000$.

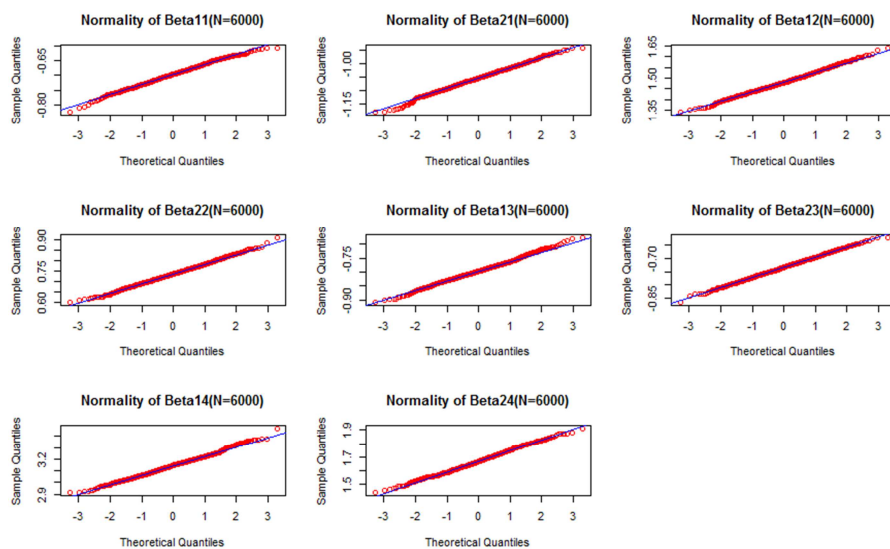


Figure 3. Normality qq-plot of Multinomial Logistic Regression Parameter Estimates when $N=6,000$.

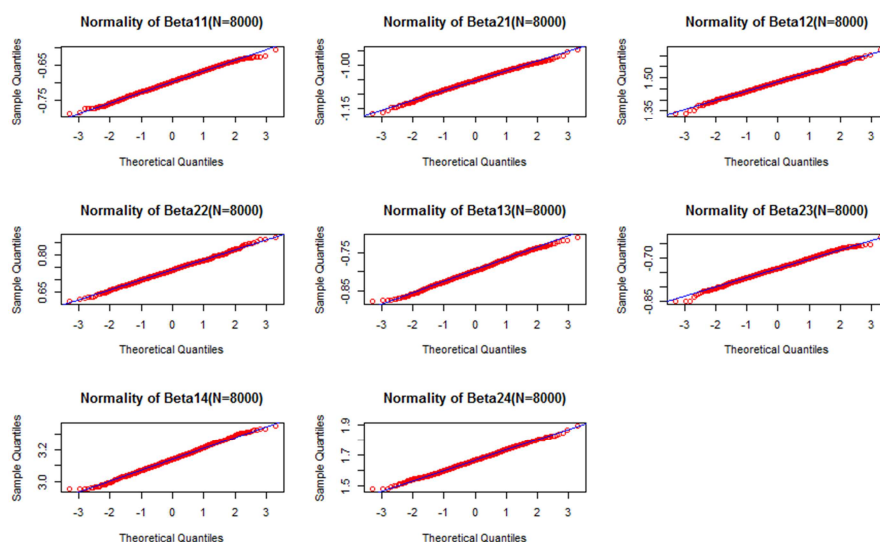


Figure 4. Normality qq-plot of Multinomial Logistic Regression Parameter Estimates when $N=8,000$.

5. Conclusions and Recommendations

Modern contraceptive method is the most preferred method of contraceptive among women, an indication that more women still embrace safe contraception. Marital status, Education level, wealth index, area of residence and the number of children a woman has, highly influences the particular contraceptive method to use. However, religion, access to a health facility and age are not key factors a woman would consider while deciding on the particular contraceptive method to use. Multinomial Logistic Regression parameter estimates are consistent estimators and assume a normal distribution as sample size increases. This however requires a very large sample size if consistency and normality are to be achieved.

Government and stakeholders effort of providing modern contraceptives to women especially those with primary or no education and those in poorest, poorer and middle wealth quintiles should be intensified to increase compliance of the World Health Organization (WHO) recommended inter-pregnancy interval, a key factor in reducing maternal and perinatal mortality. Initiatives such as mobile health facilities to enhance education of women on the best choices of contraception should be enhanced. Inclusion of Muslim leaders and Catholic clerics in planning and execution of contraceptive related matters should be emphasized in order to convince more women to embrace contraception.

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