MODELLING OF MATERNAL HEALTH CARE SERVICES USING MULTINOMIAL LOGISTIC REGRESSION

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ABSTRACT
Several methods which have been adopted to analyze multi-category data yields unsatisfactory results because of strict assumptions regarding normality, linearity, and homoscedasticity. As a result, Multinomial logistic regression is considered as an alternative because it does not assume normality, linearity, or homoscedasticity (Hosmer & Lemeshow, (2000)). The study attempted to use Maximum likelihood estimation and predicted probability to model Maternal Health Care Services data based on a set of explanatory variables. Also to determine the indices that affect Mortality rate. The result shows that wealth index has a significant impact on the use of public and private health delivery facilities. Educational level, antenatal care, assistance during delivery and place of residence are also important factors in assessing Maternal Health Care Services. Finally, the study revealed that educated women, who are wealthy, living in urban areas and who received antenatal care services and assistance during delivery are more likely to utilize Maternal Health Care Services (MHCS)

Keywords: Multinomial Logit Regression, Multi-category data, Maternal Health Services, binomial logit, Maximum likelihood estimates

INTRODUCTION

World Health Organisation (2004) stated that maternal healthcare services include the availability of preconception, prenatal, and postnatal care to reduce maternal morbidity and mortality of pregnant women. This involves monitoring and maintaining the progress during and after pregnancy, labour and delivery exercise of a pregnant women. According to Adams et al. (2005) societies like Nigeria with high poverty level; low level of education, poor economic status and congested place of abode are factors responsible for high mortality rate among women. This was supported by the World Health Organization (2010) which estimated that 587,000 maternal deaths occur in Sub-Saharan Africa, with Nigeria accounting for about 10% of all maternal deaths globally. In all modeling of maternal health care data involves much risk which includes creating awareness, identification, monitoring, reporting, planning and mitigation and other indirectly related services. The maternal healthcare data are categorical dependent variables which include one or more independent variables and are usually (but not necessarily) continuous and normally use probability scores as the predicted values of the dependent variable. The data, either categorical or continuous, can be modeled using multinomial logistic regression. The problem of Modeling of Health Services Data Using Multiple Logistic Regression is based on the use of binomial logistic regression model of two variables which has failed to address a multi-category response situation.

Multinomial logistic regression is a simple extension of binary logistic regression that allows for more than two categories of the dependent or outcome variable. Like binary logistic regression, multinomial logistic regression uses maximum likelihood estimation to evaluate the probability of categorical membership. Multinomial logistic regression does necessitate careful consideration of the sample size and examination for outlying cases. Like other data analysis procedures, initial data analysis should be thorough and include careful univariate, bivariate, and multivariate assessment.
The basic principle of multinomial logistic regression is similar to that of binomial logistic regression, as it is based on the probability of membership of each category of the dependent variable. The

multinomial logistic regression (MLR) compares the probability of each of j-1 categories to a baseline or reference category. In a way, we can say that we are fitting j-1 separate binary logistic models, where we compare category one to the baseline category, category two to the baseline and so on. In practice software, algorithms allow the user to model the comparisons to the baseline simultaneously using maximum likelihood estimation, which is better because doing it sequentially could lead to misestimating the standard errors. This paper attempted to model Maternal Health Care Services (MHCS) data using maximum likelihood estimates, predicted probability and assesses the fit and significance of the predictors of the MLR based on a set of explanatory variables. Also, the study attempted to determine the indices that affect Mortality rate using multinomial logistic regression model that takes care of multi-category response.

Mathematically, a multinomial logit model is a combination of binomial logit models, all compared against a reference alternative. The basic concept of multinomial logistic regression was generalized from binary logistic regression, in the sense that it is based on the probability of membership of each group of the response variable.

The logistic regression model assumes that the categorical response variable has only two values; 1 for success and 0 for failure. The logistic regression model can be extended to situations where the response variable has more than two values, and there is no natural ordering of the categories. Natural ordering can be treated as nominal scale; such data can be analyzed by slightly modified methods used in dichotomous outcomes which is called the multinomial logistic regression. Let π_j denote the multinomial probability of an observation falling in the j^{th} category, to find the relationship between this probability and the p explanatory variables, X_1, $X_{2,\dots}$, X_p. The multiple logistic regression models is

$$\log\left[\frac{\pi_j(\mathrm{x}_i)}{\pi_c(\mathrm{x}_i)}\right] = \alpha_{oi} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \dots + \beta_{pj}x_{pi}, \tag{1}$$

where j = 1, 2,...,(c - l), i = 1, 2, ... , n. Since all the π's add to unity, this reduces to

$$[\pi_j(\mathrm{x}_i)] = \frac{\exp\left(\alpha_{oi}+\beta_{1j}x_{1i}+\dots+\beta_{pj}x_{pi}\right)}{1+\sum_{j=1}^{c-1}\exp\left(\alpha_{oi}+\beta_{1j}x_{1i}+\dots+\beta_{pj}x_{pi}\right)} \tag{2}$$

j = 1, 2, . . . ,(c-1), the model parameters are estimated by the Maximum Likelihood(ML) method.

In MLR model, the estimate for the parameter can be identified compared to a baseline category. We defined bold letter as matrix or vector, let π_j (**x**) = p(Y = j | **x**) at a fixed setting **x** for explanatory variables, with $\sum_j \pi_j$=1, for observations at that setting, we treat the counts at the J categories of Y as multinomial with probabilities, {π_1 (**x**), … , π_J (**x**) }. Logit models pair each response category with a baseline category, often the most common model is:

$$\log\left[\frac{\pi_j\ (\mathbf{x})}{\pi_J\ (\mathbf{x})}\right] = \alpha_j + \acute{\beta}_j\mathrm{x} \tag{3}$$

where j = 1,…, (J −1), simultaneously describe the effects of **x** on these (J-1) logits. The effects vary according to the response paired with the baseline and these (J-1) equations determine parameters for logits with other pairs of response categories. Since

$$\log\left[\frac{\pi_a\ (\mathbf{x})}{\pi_b\ (\mathbf{x})}\right] = \log\left[\frac{\pi_a\ (\mathbf{x})}{\pi_J\ (\mathbf{x})}\right] - log\left[\frac{\pi_b\ (\mathbf{x})}{\pi_J\ (\mathbf{x})}\right] \tag{4}$$

with categorical predictors, Pearson Chi-square statistic, χ^2 and the likelihood ratio Chi-square statistic, G^2, goodness-of-fit statistics provide a model check when data are not sparse. When an explanatory variable is continuous or the data are sparse, such statistics are still valid for comparing nested models differing by relatively few terms, Agresti (2007).

Estimating Multinomial Response Probabilities

The equation that expresses multinomial logit models directly in terms of response probabilities is given by

$$\pi_j(\mathbf{x}) = \frac{\exp(\alpha_j + \beta_j{}'x)}{1+\sum_{h=1}^{J-1}\exp(\alpha_h + \beta_h{}'x)} \quad (5)$$

with $\alpha_J = 0$ *and* $\beta_J = 0$. This follows from the equation

$$\log\left[\frac{\pi_j(\mathbf{x})}{\pi_J(\mathbf{x})}\right] = \alpha_j + \beta_j{}'x, \quad j=1,\ldots,(J-1) \quad (6)$$

This also holds with j = J by setting $\alpha_J = 0$ *and* $\beta_J = 0$. Setting the parameters equal to zero for a baseline category for identifiable reasons, the numerators for various j sum to the denominator, so $\sum_j \pi_j$=1, for (J = 2), simplifies to the formula used for binary logistic regression, Agresti (2007).

The general MLR model proposed by Moutinho and Hutcheson (2011) is expressed as:

$$\log\left[\frac{\Pr(Y=j)}{\Pr(Y=j)}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \quad (7)$$

The model of utilizing maternal health care services between the two places of deliveries can therefore, be represented using two (i.e., j -1) logit models.

$$\log\left[\frac{\Pr(Y=\text{Public health facility})}{\Pr(Y=\text{Home})}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \quad (8)$$

$$\log\left[\frac{\Pr(Y=\text{Private health facility})}{\Pr(Y=\text{Home})}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \quad (9)$$

The intercept β_0 is the value of the response category when all the explanatory variables are equal to zero. β_1, β_2,…, β_k are the regression coefficients of $x_1, x_2, \ldots, x_k$. Each of the regression coefficients explains the size of the contribution of risk factor x_i relative to a baseline category. A negative regression coefficient means that the independent variable reduces the probability of the outcome, while a positive regression coefficient means that the variable increases the probability of that outcome Bhadra (2005), Washington et al. (2011) and Moutinho et al, (2011); a large regression coefficient means that the risk factor strongly favours the probability of that outcome, while a near-zero regression coefficient means that the risk factor has little influence on the probability of that outcome (Petrucci (2009) and Moutinho et al, (2011)).

We denote the probability that a woman delivered at home (baseline category) by π_0 and this is estimated by $\hat{\pi}_0$. The probability that a woman delivered at a public health facility is denoted by π_1 and the estimate by $\hat{\pi}_1$. The probability that a woman delivered at a private health facility is denoted by π_2 and is estimated by $\hat{\pi}_2$, the response probabilities satisfying $\sum_{j=0}^{2} \pi_j$=1, our baseline category is (home=0). From the parameter estimates, we can calculate these probabilities by two steps:

First, we can calculate $\log\left[\frac{\hat{\pi}_1}{\hat{\pi}_0}\right]$ *and* $\log\left[\frac{\hat{\pi}_2}{\hat{\pi}_0}\right]$ as the response variable has three categories, which means that there are 2 equations as follows:

Let $Y_1 = \log\left[\frac{\overset{\Lambda}{\pi_1}}{\overset{\Lambda}{\pi_0}}\right]$ *and* $Y_2 = \log\left[\frac{\overset{\Lambda}{\pi_2}}{\overset{\Lambda}{\pi_0}}\right]$

We now calculate $\hat{\pi}_1$, $\hat{\pi}_2$ and $\hat{\pi}_0$ as follows, where exponential (e) = 2.71828 is the base of the system of natural logarithms:

$$\hat{\pi}_1 = \frac{\exp(y_1)}{1 + \exp(y_1) + \exp(y_2)} \tag{10}$$

$$\hat{\pi}_2 = \frac{\exp(y_2)}{1 + \exp(y_1) + \exp(y_2)} \tag{11}$$

$$\hat{\pi}_0 = \frac{1}{1 + \exp(y_1) + \exp(y_2)} \tag{12}$$

Where the (1) term in each denominator and in the numerator of $\hat{\pi}_0$ represents

exp ($\hat{\alpha}_o + \hat{\beta}_o$ x), for $\hat{\alpha}_o = \hat{\beta}_o = 0$, Agresti (2007). $\hat{\pi}_1$, $\hat{\pi}_2$ and $\hat{\pi}_0$ give the various probabilities of any case the in group. The interpretation of ß can be done using the odds ratios concept. Exponenting the regression coefficient β_j for predictor X_j yields the odds ratio (e^{β_j}). Odds ratio is the change in the odds of Y given a unit change in X_j when all other explanatory variables are held constant.

METHODOLOGY

The data for this work was extracted from the Nigeria Demographic Health Survey (NDHS) 2008. It is a nationally representative survey of 33,385 women of age 15-49 years. The unit of analysis for this study is Every Married Woman (EMW) who had at least one live birth in the last five years preceding the survey. The sample size for this study consists of 18, 028. Every Married Woman (EMW). The SPSS (version 20) software was used to compute the maximum likelihood estimation of the model parameters through the Newton- Raphson's iterative procedure. The variables considered are: X_{10} =Age Group(15-19yrs), X_{11}=Age Group(20-29yrs), X_{12}=Age Group(30-39yrs), X_{20}= Urban Resident, X_{21}=Rural resident X_{30}=No Education, X_{31}=Primary Education, X_{32}=Secondary Education, X_{33}= Higher Education, X_{42}=Traditionalist, X_{50}= Wealth Index (poorest), X_{51}= Wealth Index (poorer), X_{52}= Wealth Index (middle), X_{53}=Wealth Index (richer), X_{60}= Antenatal Care, X_{70}=Assistance During Delivery.

RESULTS

Table 1 shows the result of AIC and BIC of the model fitted to judge the closeness. The result shows that our model AIC, BIC and -2log likelihood are very close, therefore, the smaller the value, the better the fit. The Chi-square value was also computed. The result in Table 2 shows that Chi-square statistic is significant: χ^2 (32) = 10212.429, $p < .000$, which indicates that the full model is better, or accurate. Also, the deviance test was also considered, the result shows that the model was well-fitted and has non-significant deviance.

Table 1: Model Fitting Information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2Log Likelihood	Chi-Square	Df	Sig.
Intercept Only	13231.966	13247.536	13227.966			
Final	3083.537	3348.232	3015.537	10212.429	32	.000

Table 2: Goodness-of-Fit

	Chi-Square	Df	Sig.
Pearson	2343.892	1702	.000
Deviance	1338.045	1702	1.000

Table 3 is the Nagelkerke's measure of the strength of relationship between the dependent variable and the explanatory variables. The result shows a (52.9%) moderate relationship between the predictors and the prediction

Table 3: Pseudo R-Square Square

Cox and Snell	.437
Nagelkerke	.529
McFadden	.328

Table 4 is the likelihood ratio test of the model which shows that the variables age, religion, wealth index, antenatal care, assistance during delivery, type of place of residence and highest level of education. The result shows that all the variables mentioned above are all significant contributors to explaining differences in place of delivery. The values of the -2log likelihood of reduced model obtained for the variables are such as: antenatal care (4155.519), assistance during delivery (3763.809), wealth index (3665.984), educational level (3417.204), religion (3257.855), place of residence (3055.744) and age (3044.265). The chi-square statistic obtained showed that the model is significance.

Table 4: Likelihood Ratio Tests

Effect	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	Df	Sig.
Intercept	3083.537	3348.232	3015.537[a]	.000	0	.
Age	3100.265	3318.249	3044.265	28.728	6	.000
Religion	3313.855	3531.839	3257.855	242.318	6	.000
Wealth index	3717.984	3920.398	3665.984	650.447	8	.000
Antenatal care	4219.519	4468.644	4155.519	1139.983	2	.000
Assistance	3827.809	4076.933	3763.809	748.272	2	.000
Residence	3119.744	3368.869	3055.744	40.207	2	.000
Educational level	3473.204	3691.189	3417.204	401.668	6	.000

The Logit Regression Parameters of the model that were estimated as shown in the model below:

$$\log\left[\frac{\Pr(\text{Public health facility})}{\Pr(\text{Home})}\right] = -3.077-0.097X_{12}+0.188X_{20}-1.822X_{30}-1.383X_{31}-0.866X_{32}-1.666X_{42}-1.909X_{50}-1.494X_{51}-1.095X_{52}-0.539X_{53}+2.113X_{60}+3.869X_{70} \quad (13)$$

This implies that a woman of the age group (15-19 yrs) has a lower probability of delivering at a public health facility rather than women between the ages (40-49yrs). A woman who is an urban resident has higher probability of delivering at a public health facility than women in the rural area. A woman with no educational background primary/secondary but uses public health facility has a lower probability health maternal care, compared to a woman with higher education. A woman within the wealth index (poorest/poorer) has a lower probability of delivering at a public health facility than a woman with the wealth index (richest). A woman who receives antenatal care has an higher probability of delivering at a public health facility than those who do not receive.

$$\log\left[\frac{\Pr(\text{Private health facility})}{\Pr(\text{Home})}\right] = -1.774-0.398X_{10}-0.258X_{11}-0.425X_{20}-1.984X_{30}-1.017X_{31}-0.590X_{32}-1.622X_{41}-2.283X_{50}-2.012X_{51}-1.613X_{52}-1.00X_{53}+1.955X_{60}+2.487X_{70} \quad (14)$$

The result of the model above states that woman within the age group of (15-19yrs) has a lower probability of delivering at a private health facility rather than a woman between (40-49 yrs). A woman who lives in an urban area and uses private health facility has higher probability of delivering than a woman in the rural area. The probability of a woman who delivered at a private health facility with no education/primary/secondary is lower compared to a woman with a higher education. A woman with poorest/poorer wealth index has a lower probability of delivering at a private health facility than a woman with rich wealth index. Also, a woman with good antenatal care has higher probability of delivering at a private health facility than a woman who does not. Finally, a woman with assistance during delivery has higher probability of delivering at a private health facility than those who do not.

PREDICTIONS FROM THE MLR MODEL

Predicted probability of utilizing MHCS through delivery at a public health facility and private health is calculated using variables that were consistent. The result showed that there is a strong association in the MLR model. The following variables are used: antenatal care, place of residence, wealth-index, educational level and assistance during delivery. The data was modeled using predicted model of equation 15 and 16.

$$\log\left[\frac{\Pr(\text{Public health facility})}{\Pr(\text{Home})}\right] = -3.979+0.155X_{20}-1.931X_{30}-1.416X_{31}-0.900X_{32}-1.904X_{50}-1.495X_{51}-1.088X_{52}-0.545X_{53}+2.136X_{60}+3.881X_{70} \quad (15)$$

$$\log\left[\frac{\Pr(\text{Private health facility})}{\Pr(\text{Home})}\right] = -2.980+0.301X_{20}-2.581X_{30}-1.209X_{31}-0.682X_{32}-2.184X_{50}-1.931X_{51}-1.532X_{52}-0.996X_{53}+2.022X_{60}+2.715X_{70} \quad (16)$$

Table 5: Predicted probabilities for Some Selected Cases

					Probabilities of Utilizing MHCS		
Place of Residence	Educational Level	Wealth Index	Antenatal Care	Assistance During Delivery	Public Health Facility	Private Health Facility	Home
Rural	No Education	Poorest	Yes	Yes	0.14	0.04	0.82
Rural	No Education	Poorest	No	No	0.00	0.00	1.00
Urban	Primary	Richest	Yes	Yes	0.39	0.42	0.18
Urban	Higher	Richer	Yes	Yes	0.57	0.32	0.11

A lot of information can be gained from the predicted probabilities presented in Table 5. For example, Women who are Rural Residents are more likely to deliver at home with probabilities (1.00, 0.82) compared to Urban Residents. The probabilities show that women who are educated are more likely to deliver at both public and private health facilities with probabilities 0.57, 0.39, 0.42 and 0.32 respectively compared to the uneducated ones. The effect of wealth index is particularly noticeable when compared to delivery at public and private health facilities.

DISCUSSION OF RESULTS

The odd ratio was computed for both public and private health services, see Appendix 2 (Table 7) and the result were 0.903 and 0.671 for ages 15-19, 0.746 and 0.772 for ages 20-29 and 0.907 and 0.922 for ages 30-39. Also the case of the Religion, Wealth index and Educational level were computed. The predicted MLR was also considered for a woman of the age group (15-19 yrs) the result shows a lower probability of delivering at a public health facility rather than women between the ages (40-49 yrs). A woman who is an urban resident has higher probability of delivering at a public health facility than women in the rural area. A woman with no educational background primary/secondary but uses public health facility has lower probability of maternal health care, compared to a woman with higher education. A woman within the wealth index (poorest/poorer) has a lower probability of delivering at a public health facility than a woman with the wealth index (richest). A woman who receives antenatal care has higher probability of delivering at a public health facility than those who do not receive. The MLR predicted model was also considered for the case of the public health facilities. The estimated MLR model 13-16 show that there was an increase of 0.155 by the influence of rural and urban use of heath facilities, 2.136 for antenatal and 3.881 for assistance received during delivery. Also, the private sector was considered, it was predicted that the private facilities has an increase probability of 0.301 urban used of heath facilities than the rural. The predicted rate of antenatal and assistance during delivery for the private health facilities were 2.022 and 2.715 respectively while the predicted indices for wealth and education are on the decrease for both public and private health facilities.

CONCLUSION

The model was able to reveal that wealth index has a significant impact particularly for the comparison between delivery at public and private health facilities. Educational level, antenatal care, assistance during delivery and place of residence are also important factors in Maternal Health Care Services. These factors assist in distinguishing between places of delivery and the wealth index of a woman. Finally, the educated women who are wealthy, living in urban areas and who received antenatal care and assistance during delivery are more likely to utilize MHCS. As a result, we recommend that there should be increase in the awareness programmes for maternal mothers and all women should be encouraged to have at least secondary School certificate.

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Appendix 1 **Table 6: Baseline characteristics of ever married woman (NDHS, 2008)***

Variable	N= 18028	Variable	N= 18028
Place of delivery (%)		Wealth Index (%)	
Home	65.4	Poorest	26.3
Public health facility	20.8	Poorer	23.5
Private health facility	13.8	Middle	19.5
Age group of respondents (%)		Richer	16.9
15-19	7	Richest	13.8
20-29	46.2	Place of residence (%)	
30-39	34.9	Urban	26.8
40-49	12	Rural	73.2
Education respondent (%)		Antenatal care (%)	
No education	49	Received antenatal care (yes)	61.1
Primary education	22.7	No antenatal care (no)	38.9
Secondary education	23.2	Assistance during delivery (%)	
Higher education	5.2	Received assistance during delivery (yes)	81.4
Religion (%)		No assistance during delivery (no)	18.6
Christian	42.5	Region (%)	
Islam	55.5	North central	18.6
Traditionalist	1.9	North east	22.1
Other	0.1	North west	27
		South east	8.1
		South south	11.7
		South west	12.6

Source: Nigeria Demographic Health Survey (NDHS)

Appendix 2 Table 7: Public and private health facilities Odds Ratios (OR) of ever married women across selected covariates (NDHS, 2008)

Variable	Public OR & 95% CI	Private OR & 95% CI
Age group of respondents		
15-19	0.903 (0.717, 1.136)	0.671 (0.493, 0.915)
20-29	0.746 (0.638, 0.872)	0.772 (0.641, 0.931)
30-39	0.907 (0.773, 1.064)	0.922(0.763, 1.116)
40-49	1	1
Education respondent		
No education	0.162 (0.123, 0.213)	0.138 (0.101, 0.187)
Primary education	0.251(0.193, 0.326)	0.362 (0.274, 0.477)
Secondary education	0.421 (0.325, 0.544)	0.554 (0.424, 0.724)
Higher education	1	1
Religion		
Christian	0.512 (0.162, 1.623)	0.525 (0.153, 1.798)
Islam	0.431 (0.136, 1.367)	0.197 (0.058, 0.678)
Traditionalist	0.189 (0.054, 0.662)	0.295 (0.079, 1.107)
Wealth Index		
Poorest	0.148 (0.12, 0.184)	0.102 (0.079, 0.131)
Poorer	0.224 (0.185, 0.272)	0.134 (0.107, 0.167)
Middle	0.335 (0.281, 0.398)	0.199 (0.164, 0.241)
Richer	0.583 (0.495, 0.687)	0.368 (0.309, 0.438)
Richest	1	1
Place of residence		
Urban	1.207(1.077, 1.352)	1.529 (1.342, 1.742)
Rural	1	1
Antenatal care		
Received antenatal care (yes)	8.272 (7.022, 9.744)	7.062 (5.662, 8.808)
No antenatal care (no)	1	1
Assistance during delivery		
Received assistance during delivery (yes)	47.907 (26.91, 85.287)	12.026 (7.7, 18.781)
No assistance during delivery (no)	1	1

Appendix 3 Table 8:Parameter Estimates for Logit Equation
Models 13& 14

Place of delivery		B	Std. Error	Wald	Df	Sig.	Exp(B)	95% C.I for Exp(B)	
								Lower Bound	Upper Bound
PUBLIC HEALTH FACILITY	Intercept	-3.077	0.673	20.922	1	0.000			
	[Age=1]	-0.102	0.117	0.762	1	0.383	0.903	0.717	1.136
	[Age=2]	-0.293	0.08	13.558	1	0.000	0.746	0.638	0.872
	[Age=4]	-0.097	0.082	1.428	1	0.232	0.907	0.773	1.064
	[Age=6]	0^b	.	.	0	.	.	.	.
	[Residence=1]	0.188	0.058	10.547	1	0.001	1.207	1.077	1.352
	[Residence=2]	0^b	.	.	0	.	.	.	.
	[Edulevel=0]	-1.822	0.14	168.604	1	0.000	0.162	0.123	0.213
	[Edulevel=1]	-1.383	0.134	106.057	1	0.000	0.251	0.193	0.326
	[Edulevel=2]	-0.866	0.131	43.511	1	0.000	0.421	0.325	0.544
	[Edulevel=3]	0^b	.	.	0	.	.	.	.
	[Religion=2]	-0.669	0.588	1.292	1	0.256	0.512	0.162	1.623
	[Religion=3]	-0.842	0.589	2.043	1	0.153	0.431	0.136	1.367
	[Religion=4]	-1.666	0.639	6.786	1	0.009	0.189	0.054	0.662
	[Religion=6]	0^b	.	.	0	.	.	.	.
	[Wealthind=1]	-1.909	0.11	303.164	1	0.000	0.148	0.12	0.184
	[Wealth_ind=2]	-1.494	0.098	234.707	1	0.000	0.224	0.185	0.272
	[Wealthind=3]	-1.095	0.089	152.36	1	0.000	0.335	0.281	0.398
	[Wealthind=4]	-0.539	0.083	41.975	1	0.000	0.583	0.495	0.687
	[Wealthind=5]	0^b	.	.	0	.	.	.	.
	[Antecare=0]	2.113	0.084	639.227	1	0.000	8.272	7.022	9.744
	[Antecare=1]	0^b	.	.	0	.	.	.	.
	[Assistance=0]	3.869	0.294	172.881	1	0.000	47.907	26.91	85.287
	[Assistance=1]	0^b	.	.	0	.	.	.	.

Continuation of Table 8: Parameter Estimates for Logit Models 13 & 14

PRIVATE HEALTH FACILITY	Intercept	-1.774	0.687	6.669	1	0.01			
	[Age=1]	-0.398	0.158	6.352	1	0.012	0.671	0.493	0.915
	[Age=2]	-0.258	0.095	7.319	1	0.007	0.772	0.641	0.931
	[Age=4]	-0.081	0.097	0.689	1	0.406	0.922	0.763	1.116
	[Age=6]	0^b	.	.	0	.	.	.	.
	[Residence=1]	0.425	0.067	40.518	1	0.000	1.529	1.342	1.742
	[Residence=2]	0^b	.	.	0	.	.	.	.
	[Edulevel=0]	-1.984	0.158	157.985	1	0.000	0.138	0.101	0.187
	[Edulevel=1]	-1.017	0.141	51.699	1	0.000	0.362	0.274	0.477
	[Edulevel=2]	-0.59	0.137	18.633	1	0.000	0.554	0.424	0.724
	[Edulevel=3]	0^b	.	.	0	.	.	.	.
	[Religion=2]	-0.644	0.628	1.053	1	0.305	0.525	0.153	1.798
	[Religion=3]	-1.622	0.63	6.638	1	0.01	0.197	0.058	0.678
	[Religion=4]	-1.221	0.675	3.275	1	0.07	0.295	0.079	1.107
	[Religion=96]	0^b	.	.	0	.	.	.	.
	[Wealthind=1]	-2.283	0.129	312.127	1	0.000	0.102	0.079	0.131
	[Wealthind=2]	-2.012	0.112	320.019	1	0.000	0.134	0.107	0.167
	[Wealthind=3]	-1.613	0.098	270.023	1	0.000	0.199	0.164	0.241
	[Wealthind=4]	-1	0.089	126.341	1	0.000	0.368	0.309	0.438
	[Wealthind=5]	0^b	.	.	0	.	.	.	.
	[Antecare=0]	1.955	0.113	300.766	1	0.000	7.062	5.662	8.808
	[Antcare=1]	0^b	.	.	0	.	.	.	.
	[Assistance=0]	2.487	0.227	119.565	1	0.000	12.026	7.7	18.781
	[Assistance=1]	0^b	.	.	0	.	.	.	.

Source: Nigeria Demographic Health Survey (NDHS) 2008

Appendix 4 Table 9: Parameter Estimates for Predicted logit equation model 15 & 16

								Lower Bound	Upper Bound
PUBLIC HEALTH FACILITY	Intercept	-3.979	0.328	147.109	1	0.000			
	[Residence=1]	0.155	0.057	7.367	1	0.007	1.168	1.044	1.307
	[Residence=2]	0b	.	.	0	.	.	.	.
	[Edulevel=0]	-1.931	0.135	203.743	1	0.000	0.145	0.111	0.189
	[Edulevel=1]	-1.416	0.133	113.02	1	0.000	0.243	0.187	0.315
	[Edulevel=2]	-0.9	0.13	47.814	1	0.000	0.407	0.315	0.525
	[Edu level=3]	0b	.	.	0	.	.	.	.
	[Wealth index=1]	-1.904	0.109	307.249	1	0.000	0.149	0.12	0.184
	[Wealth index=2]	-1.495	0.097	239.116	1	0.000	0.224	0.185	0.271
	[Wealth index=3]	-1.088	0.088	152.441	1	0.000	0.337	0.283	0.4
	[Wealth index=4]	-0.545	0.083	43.165	1	0.000	0.58	0.493	0.682
	[Wealthindex=5]	0^b	.	.	0	.	.	.	.
	[Antecare=0]	2.136	0.083	657.78	1	0.000	8.465	7.19	9.966
	[Antecare=1]	0^b	.	.	0	.	.	.	.
	[Assistance=0]	3.881	0.294	174.584	1	0.000	48.449	27.246	86.154
	[Assistance=1]	0^b	.	.	0	.	.	.	.
PRIVATE HEALTH FACILITY	Intercept	-2.98	0.279	113.934	1	0.000			
	[Residence=1]	0.301	0.065	21.127	1	0.000	1.351	1.188	1.535
	[Residence=2]	0^b	.	.	0	.	.	.	.
	[Edulevel=0]	-2.581	0.151	290.957	1	0.000	0.076	0.056	0.102
	[Edulevel=1]	-1.209	0.139	75.45	1	0.000	0.298	0.227	0.392
	[Edulevel=2]	-0.682	0.135	25.677	1	0.000	0.506	0.388	0.658
	[Edulevel=3]	0^b	.	.	0	.	.	.	.
	[Wealthindex=1]	-2.184	0.127	294.347	1	0.000	0.113	0.088	0.144
	[Wealthindex=2]	-1.931	0.11	305.425	1	0.000	0.145	0.117	0.18
	[Wealthindex=3]	-1.532	0.096	252.497	1	0.000	0.216	0.179	0.261
	[Wealthindex=4]	-0.996	0.088	129.531	1	0.000	0.369	0.311	0.438
	[Wealthindex=5]	0^b	.	.	0	.	.	.	.
	[Antecare=0]	2.022	0.112	325.131	1	0.000	7.556	6.065	9.414
	[Antecare=1]	0^b	.	.	0	.	.	.	.
	[Assistance=0]	2.715	0.226	144.814	1	0.000	15.105	9.707	23.506
	[Assistance=1]	0^b	.	.	0	.	.	.	.