

"MODELING FACTORS THAT INFLUENCES PLACE OF  
MATERNAL DELIVERY IN KENYA"

BY

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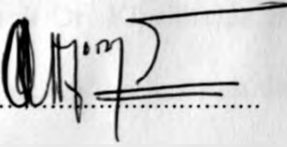
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## Declaration by Student

I the undersigned declare that this project is my original work and to the best of my knowledge has not been submitted for the award of degree in any other University.

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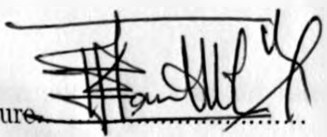
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Date.....17<sup>th</sup> SEPTEMBER, 2010

## Declaration by supervisors

This project has been submitted for examination with my approval as the University supervisor.

DR.KIPCHIRCHIR I. CHUMBA

Signature.....

Date.....17-9-2010

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# Dedication

This project is dedicated to my daughter Vivian Njoroge for her endurance of my absence while undertaking the study. I feel so indebted to her mum Milcah Warigia and my Mum Njoki Mungai for their care, support and providing a conducive studying atmosphere.

## Abstract

The study aims to examine factors that influence the place of delivery among pregnant women in the country. The study used secondary data source from the Kenya National Bureau of Statistics (KNBS) Kenya Demographic Surveys (KDHS) 2008 for analysis. In regard to maternal health: antenatal care, Delivery care, place of delivery and maternal mortality data was captured during the survey.

On data analysis, bivariate analysis with the Chi-square was used to check the variables (factors that influence) significance. All the variables identified as potentially important were considered for inclusion in the multinomial logistic regression model. To obtain an adequate parsimonious model, backward selection procedure was used. The statistical package used is SPSS version 10.

The results implied that almost all explanatory variables used in the study were statistically significant and were included in the parsimonious model to explain effects of various factors on place of maternal delivery in the country.

In conclusion, the study showed that the place of delivery in the Kenya is determined by a wide range of factors. The factors that influence place of maternal delivery in Kenya include socio economic, demographic status, cultural and reproductive behaviors. The study further recommended a study to determine the significance of place of delivery on maternal mortality.

# Abbreviations

**KNBS** : Kenya National Bureau of Statistics

**KDHS** : Kenya Demographic and Health Survey

**MDGs** : Millennium Development Goals

**MMR** : Maternal Mortality Ratio

**UN** : United Nations

**NRHS** : National Reproductive Health Services

**WHO** : World Health Organization

**AMREF** : Africa Medical and Research Foundation

**GNP** : Gross National Product

**VA** : Verbal Autopsy

**PMMN** : Prevention of Maternal Mortality Network

**SPSS** : Statistical Package for Social Scientists

**OR** : Odd Ratio

**EOC : Emergency Obstetric Care**

**TBA : Traditional Birth Attendant**

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# Chapter 1

## INTRODUCTION

### 1.1 Background

Maternal Health is the biggest challenges of the 21st century with the impact spreading from developing to the developed countries. In a rapidly globalizing world economy, there is a growing consensus to return population to the path of stability for economic Development through addressing Millennium Development Goals (MDGs) and among other international conventions.

Globally, every year, more than 500,000 maternal deaths occur worldwide, 4 million newborns die and another 3 million babies are stillborn. Nearly all these deaths take place in low and middle-income countries and most could be prevented with current medical care. As dramatic as these statistics are, it only indicates part of the story since many other women experience substantial suffering and permanent injury as a result of pregnancy and childbirth.

Most obstetric complications occur around the time of delivery and cannot be predicted.

Therefore, it is important that all pregnant women have access to a skilled attendant ,skilled attendance at delivery is advocated as the single most important factor in preventing maternal deaths and the proportion of births attended by skilled health personnel is one of the indicators for Millennium Development Goal 5 on Improved Maternal Health. Access to skilled delivery care is also crucial to prevent stillbirths and to improve newborn survival. Skilled attendants can perform deliveries either at home, in health centres or in hospitals, but it is argued that the most efficient strategy for lower-income countries is to place them in health centres with referral capacity. In practice, skilled attendance in most countries is synonymous with facility delivery. The United Nations (UN) and the World Health Organization (WHO) recommend skilled attendance to every birth as the single most critical intervention for ensuring safe motherhood (Collin, et al, (2006)). Access to affordable, comprehensive and efficient care during pregnancy and especially at delivery seems to be the crucial factor in explaining the disparity in maternal morbidity and mortality between the developing countries and the developed world (Wagle et al (2004)).

Recent estimates suggest that more than 500,000 women die annually of pregnancy related complications,99% of those deaths occur in less developed regions particularly Africa and Asia. In addition, 3.9 million newborn and 3 million still births are lost each year. Majority of the maternal deaths that occur are avoidable or preventable. An emerging consensus has it that, these deaths can be prevented if deliveries are overseen by skill attendants (World Population Prospect, (2002)). However, it has been estimated that only 50% of women in the world have access to such skilled care. Maternal deaths are strongly associated with inadequate medical care at the time of delivery.

In developing countries, most women deliver at home for some reasons. In a study by Wilson

et al (1999), the identified reasons for non utilization of obstetric services include: financial constraints, lack of awareness of maternity waiting homes, no perceived need for such services, preference for home delivery because it is much less expensive. Recent Demographic and Health Survey (DHS) data from more than 50 developing countries shows that women with the limited education, knowledge of health service are less likely to use basic health services such as immunization, maternal care and family planning.

A comparison of delivery conditions in Kenya with the other countries of sub-Saharan Africa suggests that the situation in Kenya, especially in the rural areas, is fairly typical of sub-Saharan Africa (DHS 1990) with only about one-third of mothers in rural areas deliver in a health facility.

Complications related to pregnancy and child birth is a leading cause of morbidity and mortality among Kenyan women. The first authentic estimation of Maternal Mortality Ratio (MMR) was by the Kenya Demographic and Health Survey (KDHS, 1998) which estimated at 590 per 100,000 births, while KDHS 2003 reported MMR at 414 per 100,000 births. Majority of these deaths are due to direct obstetric complications including hemorrhage, sepsis, eclampsia and obstructed labour. According to the 2007 Progress Report on the Economic Recovery Strategy, the proportion of births attended by skilled health personnel (as a proxy indicator for MMR) increased from 42% in 2003 to 56% by 2007. The improvement reflects the impact of the implementation of the 1997-2010 National Reproductive Health Services (NRHS) Delivery Strategy that aims at promoting safe motherhood (family planning, antenatal obstetric care, postpartum care, newborn care and post abortion care) and child survival. In addition, KDHS 2003 shows that about 90% of the women receive any antenatal care with wide differentials by region.

To promote maternal health, appropriate delivery care is important for both maternal and perinatal health, particularly in cases where childbirth complications arise. Maternal and perinatal outcomes greatly improved when complications occur in the presence of a trained attendant. It is important that mothers deliver their babies in an appropriate setting, where professional attention and hygienic conditions can reduce the risk of complication and infections that may cause death or serious illness to either the mother or the child. Births that are delivered at home are more likely to occur without the assistance of a medically qualified person.

## 1.2 Problem Statement

Various studies have shown that the health, reproductive behaviour and socio economic status of women are among the important determinants of maternal mortality. However, comprehensive studies of factors associated with delivery care in sub-Saharan Africa settings are lacking.

Despite the fact that almost all (95 percent) of the pregnant women in Kenya receive some antenatal care from medical personnel, less than half of all the deliveries in the country take place within a health facility (National Council for Population and Development, Central Bureau of Statistics and Macro International 1994). In addition, 3282 cases had home delivery out of 5642 cases (KDHS 2008). Furthermore, the 1993 Kenya Demographic and Health Survey data show a significant improvement in antenatal care attendance in Kenya over recent years, from 80 percent in 1989 to 95 percent in 1993, whereas no improvement at all has been observed in delivery care over the same period.

## 1.3 Objectives

### Overall Objective

The overall objective of the study aimed at assessing the role of socio-economic and demographic factors in determining the place of delivery among women in Kenya.

### Specific Objectives

1. To establish significance of factors that influence place of maternal delivery in Kenya
2. To develop a parsimonious model on determinants on place of maternal delivery in Kenya

## 1.4 Significance of the Study

Majority of the maternal deaths that occur especially in developing countries are avoidable or preventable. Obermeyer and Potter (1991) and Pebley et al (1999), observed that, it is important to understand the specific factors that are important in various settings, since these may vary considerably. It is important to identify the factors which lead to either home or hospital delivery. Hence, this study aimed at determining and modeling factors that influence place of maternal delivery among women in Kenya. The study information on factors influencing place of maternal delivery is very vital for health planners and managers in order to rationally design the appropriate maternity services and inform the policies accordingly.

## Chapter 2

# LITERATURE REVIEW

Studies have shown that the health, reproductive behaviour and socio economic status of women are among the important determinants of maternal mortality. The longitudinal study by Voorhoeve et al (1984) in a low-mortality region of Kenya, factors such as distance to hospital and previous hospital delivery were observed to be related to place of delivery intentions. For the majority of women in this community, whether or not to deliver in hospital seemed mainly a question of opportunity.

A preliminary analysis involving comparisons of the distributions of the outcome variables by background characteristics such as maternal age, education level, and region of residence showed no significant difference between the analysis sample and the overall sample. The analysis is based on three-level models that take into account the pregnancy level, the woman or family level, and cluster-level effects. Multilevel logistic and multilevel multinomial regression models are used to establish determinants of place of delivery and childbirth attendant, respectively. The modeling allowed for potential correlation between the random effects and



the observed covariates.

In India, Basu (1990) noted that fear and the physical inconvenience of a hospital delivery were the predominant reasons among Indian mothers for reluctance to have hospital deliveries.

Study by Obermeyer and Potter (1991), Obermeyer (1993) Bhatia and Cleland (1995) observed factors predicting the delivery care to include cultural, socioeconomic, demographic and service accessibility factors. Low maternal or paternal educational attainment, low socioeconomic status, rural residence, young maternal age, and high-order births have been observed to be associated with high probabilities of deliveries outside a health facility. The study noted the importance of understanding the specific factors that are important in various settings, since these may vary considerably. A large number of studies on determinants of skilled attendance at delivery have investigated a plethora of potential influential factors. In their review article "Too far to walk" Thaddeus and Maine (1994) summarizes these factors under their conceptual framework of the three delays. Their focus, however, is on factors that affect the interval between the onset of an obstetric complication and its outcome, that is, on care-seeking for obstetric emergencies. Although their third delay can apply to all facility births, there is an implicit assumption in their framework that most births occur at home, which is the norm in settings with the highest mortality, and that the first and second delay occur in response to the need to change the delivery venue because of a complication.

In a study by Wilson et al (1999) the identified reasons for non utilization of obstetric services include: financial constraints, lack of awareness of maternity waiting homes, no perceived need for such services, preference for home delivery because it is much less expensive. A study on use of obstetric services in rural Nigeria shows that educational level, occupation of women, religion and occupation of the spouse were found to be the most consistent associated factors

with the use of health facilities for delivery. At the same time, maternal age and parity are not significantly associated. Gender inequality or disparities with respect to health care and education is still pronounced in many developing countries.

Magadi et al (2000) examines the determinants of delivery care and childbirth attendant in Kenya based on the 1993 Kenya Demographic and Health Survey data. The analysis utilizes multilevel logistic and multilevel multinomial regression models for the place of delivery and the type of childbirth attendant, respectively. The results show that delivery care in Kenya is determined by a wide range of factors: socioeconomic and cultural factors associated with the individual woman or her household, her demographic status or reproductive behavior relating to a specific birth, as well as availability and accessibility of health services within her community. In addition, a significant variation in delivery care behavior is observed between women and between communities, implying that there are unobserved factors within families and communities that have a significant effect on delivery care. The woman or family effect on delivery care is particularly strong, but varies by distance to the nearest delivery care facility.

According to Nuwaha and Ammoti (2004) on predictors of Home Deliveries in Rakai Districts in Uganda, 211 women from 21 clusters, who had a delivery in the previous one year, were interviewed in Rakai Districts, Uganda in 1997. The variables of interest were socio-economic, local, reproductive and self - efficacy variables and whether they delivered at home or not. Methods used were univariate analysis and stepwise multivariate analysis. The result on univariate analysis established that factors that favoured home delivery were: county, mother level of education, ethnicity, religion, father's levels of education, mother occupation, distance from maternal centre, antenatal clinic attendance, social status, attitude of the mother on delivery. On stepwise multivariate analysis, the independent variables that favour home delivery were:

county, father's occupation, previous delivery at home and social class. Conclusion was that the highest risk for current home delivery was previous home delivery with an adjusted odds ratio of 16:52. Recommendation was that in order to improve access to maternity services, educating fathers about safer delivery may discourage home delivery.

The study by Idris et al (2006), assessed the role of some health, socio-economic and demographic factors in determining the place of delivery among women in a semi-urban settlement in Zaria, north-western Nigeria. The study design was a cross sectional descriptive study conducted in Sabuwar Unguwa, Magume district Zaria Local Government Area Kaduna State Nigeria. A total of 496 women who had delivered at least once were interviewed using a pre-tested interviewer administered questionnaire.

The study revealed both high rates of home deliveries and deliveries not supervised by skilled attendants of 70% and 78% respectively. Mother's educational level, husband's occupation and age at first pregnancy were the main determinants of place of delivery. Statistically significant associations between non- formal education and home delivery, age at first pregnancy and home delivery were observed. There was no statistical significance between employment status of fathers and home delivery. In conclusion, low maternal education, unemployment among fathers, first pregnancies at less than 18 years of age increase the likelihood of home delivery in Sabuwar Unguwa, Magume district of Zaria. Girl child education, income generating activities and training of TBAs could reduce the high rate of home deliveries and its consequences in the study area.

Sabine and Campbell (2009) observed that skilled attendance at childbirth is crucial for decreasing maternal and neonatal mortality, yet many women in low- and middle-income countries deliver outside of health facilities, without skilled help. The main conceptual frame-

work in this field implicitly looks at home births with complications. They expanded this to include "preventive" facility delivery for uncomplicated childbirth, and review the kinds of determinants studied in the literature, their hypothesized mechanisms of action and the typical findings, as well as methodological difficulties encountered. The methods were reviews and ascertained relevant articles from other sources. Twenty determinants identified were grouped under four themes: (1) socio-cultural factors, (2) perceived benefit/need of skilled attendance, (3) economic accessibility and (4) physical accessibility.

The results showed ample evidence that higher maternal age, education and household wealth and lower parity increase use, as does urban residence. Facility use in the previous delivery and antenatal care use are also highly predictive of health facility use for the index delivery, though this may be due to confounding by service availability and other factors. Obstetric complications also increase use but are rarely studied. Quality of care is judged to be essential in qualitative studies but is not easily measured in surveys, or without linking facility records with women. Distance to health facilities decreases use, but is also difficult to determine. Challenges in comparing results between studies include differences in methods, context-specificity and the substantial overlap between complex variables. In conclusion, studies of the determinants of skilled attendance concentrate on socio-cultural and economic accessibility variables and neglect variables of perceived benefit/need and physical accessibility. To draw valid conclusions, the study recommended consideration of as many influential factors as possible in any analysis of delivery service use. The increasing availability of geo referenced data provides the opportunity to link health facility data with large-scale household data, enabling researchers to explore the influences of distance and service quality.

Recent Macro International Demographic and Health Survey (DHS) data from more than

50 developing countries shows that women with the limited education, knowledge of health service are less likely to use basic health services such as immunization, maternal care and family planning. Improving the knowledge of women through information, education and communication has been found to increase obstetric service utilization. Another study found that the utilization of Emergency Obstetric Care (EOC) was more than doubled following the introduction of transportation and communication system. The determinant of maternal mortality include the health and reproductive behavior of the woman, her health status, access to health services as well as her socio-economic status. It is important to identify the factors which lead to either home or hospital delivery. This study therefore, assessed the effect of education, occupation, parity, ANC attendance and age at first pregnancy, on the choice between home and hospital delivery.

## Chapter 3

# METHODOLOGY

### 3.1 Data Source

The study used secondary data source from the Kenya National Bureau of Statistics (KNBS) Kenya Demographic Surveys (KDHS) 2008 for analysis. KDHS 2008 is the latest in a series of national level population and health surveys carried out periodically after five years. The survey utilized a two stage sample based on the 1999 population and Housing Census and was designed to produce separate estimates for key indicators for each of the eight provinces in Kenya.

The KDHS 2008, was nationally representative sample of 8,195 women age 15 to 49 and 3,578 Men age 15-54 selected from 400 sample points (known as clusters) throughout Kenya, designed to provide data to monitor the population and health situation in Kenya as a follow-up of the 1989, 1993 1998, 2003 and 2008 KDHS surveys. In regard to maternal health: antenatal care, delivery care, place of delivery and maternal mortality data was captured

where maternal mortality data was obtained from the survival of respondent's sisters. The study case had 5642 respondents on place of maternal delivery.

## 3.2 Theoretical Models

In model building, the main goal is to find the parsimonious model to describe the relationship between an outcome (dependent or response) variable and a set of independent (predictor or explanatory) variables. Regression methods have become an integral component of data analysis concerned with describing the relationship between a response variable and one or more explanatory variables. The most common example of modeling and the main methods of statistical analysis for various combinations of response and explanatory variables is shown in table 3.1. \* model to be adopted for the study

i Multiple Linear regression model where the outcome variable is assumed to be continuous, taking the form,

$$Y = X_j' \beta_j = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \epsilon \quad \epsilon \sim N(0, \sigma^2) \dots \quad (3.1)$$

where  $y$  is the dependent variable and  $x$  is the independent variables while  $\beta_0$  and  $\beta_i$ 's are intercept and coefficients respectively while  $k$  is the number of explanatory variables.

### Model Assumptions

The validity of multiple linear regressions rests heavily on the following underlying assumptions

- (a) the independent (response) variable is subject to error. This error is assumed to be a random variable with mean zero

Table 3.1: Methods of statistical analysis for various combinations of response and explanatory variables

	<b>Response</b>	<b>Explanatory variables</b>	<b>Methods</b>
1.	Continuous	Binary	t -test
		Nominal, > 2 categories	Analysis of variance
		Ordinal	Analysis of Variance
		Continuous	Multiple regression
		Nominal & some continuous	Analysis of Covariance
		Categorical & continuous	Multiple regression
2.	Binary	Categorical	Contingency table Logistic regression
		Continuous	Logistic, probit model
		Categorical & continuous	Logistic regression
3.*		Nominal with > 2 categories	Nominal
	Categorical & continuous		*Nominal logistic regression
4.	Ordinal	Categorical & continuous	Ordinal logistic regression
5.	Counts	Categorical	Log-linear models
		Categorical & continuous	Poisson regression
6.	Failure times	Categorical & continuous	Survival analysis (parametric)
7.	Correlated responses	Categorical & continuous	Generalized estimating equations
			Multilevel models



(b) the predictor variables are error free

(c) the predictor variables must be linearly independent i.e. no multicollinearity

(d) the errors are uncorrelated

(e) the variance of the error is constant

(f) the error follows a normal distribution

ii logistic regression model which has become, in many fields, the standard method of analysis in the case that the outcome variable is discrete, taking two possible values 0 and

1. The model is used for prediction of the probability of occurrence of an event by fitting data to a logit function

$$\text{logit}(p) = \log\left(\frac{p}{1-p}\right) = \log\left[\frac{\text{Pr}(Y=1)}{\text{Pr}(Y=0)}\right] \quad (3.2)$$

which is a logged ratio of two probabilities

It is a generalized linear model used for binomial regression. Logistic regression, outcome variable is binary or dichotomous, taking a form of,

$$\text{Pr}(Y=1|x) = \frac{1}{1 + \exp\{-[\beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_kx_k]\}} \quad (3.3)$$

The Logit model; used to predict Logit of the dependent variable

$$\log(p/(1-p)) = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_kx_k \quad (3.4)$$

iii Poisson regression Model analysis seeks to model counts of the expected events. Just as logistic regression models the log odds of an event, Poisson regression models the (natural) log of the expected count. The logarithm of its expected value and can be

modeled by a linear combination of the independent variables. The model takes the form:

$$\log(E(Y)) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k \quad (3.5)$$

is fitted, coefficients are obtained and interpreted as in any other regression model.

Since the logarithm of the expectation of the response variable is linked to a linear function of explanatory variables we have

$$E(Y) = e^{(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k)} \quad (3.6)$$

The Poisson regression model expresses the log outcome rate as a linear function of a set of predictors.

Polytomous response models can be classified into two distinct types, depending on whether the response variable has an ordered or unordered structure. These models are ordered logit regression model and Multinomial logistic regression respectively.

iv In an ordered logistic regression model, the response  $y$  of an individual unit is restricted to one of  $m$  ordered values. The cumulative logit model assumes that the ordinal nature of the observed response is due to methodological limitations in collecting the data those results in lumping together values of an otherwise continuous response variable (McKelvey and Zavoina (1975)).

The cumulative probability for the  $i$ -th individual up to response level  $j$ , denote as  $C_{i,j}$ , can be written as

$$C_{ij} = Pr(Y_i \leq j) = \sum_{k=1}^j Pr(Y_i = k) \quad (3.7)$$

$$i = 1 \dots n, j = 1 \dots J \quad (3.8)$$

#### v Multinomial logit regression Model

As far as regression models for the analysis of categorical dependent variables with more than two response categories is concerned, several models have been considered by generalizations of logistic regression analysis to polychotomous data that is, Multinomial logistic regression is the extension for the (binary) logistic regression when the categorical dependent outcome has more than two levels, that is, unordered data with more than 2 categories. It compares multiple categories through a combination of binary logistic regressions. The category comparisons are equivalent to the comparisons for a dummy-coded dependent variable, with one category group used as the reference category.

Other Models for Nominal Outcomes are: Conditional Logit which attributes of choices can be used as predictors and Nested Logit which treats a set of choices as a hierarchy.

Consider a random variable  $Y_i$  that may take one of several discrete values, which we index  $1, 2, \dots, J$ . In the study, response is place of delivery and it takes the values 'home', 'public health facility' and 'private health facility', indexed 1, 2 and 3 respectively. Let

$$p_{ij} = Pr(Y_i = j) \quad i = 1, 2, \dots, n, j = 1, 2, \dots, J \quad (3.9)$$

denote the probability that the  $i$ -th response falls in the  $j$ -th category. In the study,  $p_{i1}$  is the probability that the  $i$ th respondent delivered at home. Assuming that the response categories

are mutually exclusive and exhaustive, then

$$\sum_{j=1}^J p_{ij} = 1 \quad (3.10)$$

for each  $i$ , that is, the probabilities add up to one for each individual, and we have only  $J - 1$  parameters. In the study case, once we know the probability of 'home delivery' and of 'delivery in public health facility' we automatically know by subtraction the probability of 'delivery in private health facility'.

For grouped data it is convenient to introduce auxiliary random variables representing counts of responses in the various categories.

Let

$n_i$  denote the number of cases in the  $i$ -th group,  $i = 1, 2, \dots, G$

$Y_{ij}$  denote the number of responses from the  $i$ -th group that fall in the  $j$ -th category, with observed value  $y_{ij}$ .

In the study  $i$  represent  $i$  group,  $n_i$  is the number of women in the  $i$ -th group, and  $y_{i1}$ ;  $y_{i2}$ ; and  $y_{i3}$  are the numbers of women who deliver at home, public hospital, and private hospital, respectively, in the  $i$ -th group. Note that

$$\sum_{j=1}^J y_{ij} = n_i \quad j = 1, 2, \dots, G \quad (3.11)$$

That is, the counts in the various response categories add up to the number of cases in each group. For individual data  $n_i = 1$  and  $y_{ij}$  becomes an indicator (or dummy) variable that takes the value 1 if the  $i$ -th response falls in the  $j$ -th category and 0 otherwise, and  $\sum_{j=1}^J y_{ij} = 1$ , since one and only one of the indicators  $y_{ij}$  can be 'on' for each case.

The probability distribution of the counts  $Y_{ij}$  given the total  $n_i$  is given by the multinomial distribution

$$Pr(Y_{i1} = y_{i1}, \dots, Y_{iJ} = y_{iJ}) = \binom{n_i}{y_{i1} \dots y_{iJ}} p_{i1}^{y_{i1}} \dots p_{iJ}^{y_{iJ}} \quad j = 1, 2, \dots, G \quad (3.12)$$

The special case where  $J = 2$  and we have only two response categories which is the binomial distribution.

Nominal logistic regression models are used when there is no natural order among the response categories. One category is arbitrarily chosen as the reference category. Suppose this is the first category. Then the logistic for the other categories are defined by

$$\text{Logit}(p_j) = \log\left(\frac{p_j}{p_1}\right) = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \dots + \beta_{kj}x_{ki}, \quad j = 2, \dots, J \quad (3.13)$$

The  $(J-1)$  logit equations are used simultaneously to estimate the parameters  $\beta_j$ . Once the parameter estimates  $\beta_j$  have been obtained, the linear predictors  $X_j'\beta_j$  can be calculated from above equation.

$$p_j = p_1 \exp\{(\beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \dots + \beta_{kj}x_{ki})\} \\ j = 2, \dots, J \quad (3.14)$$

But  $p_1 + p_2 + p_3 + \dots + p_j = 1$

so

$$p_1 = \frac{1}{1 + \sum_{j=2}^J e^{(\beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \dots + \beta_{kj}x_{ki})}} \quad (3.15)$$

and

$$p_j = \frac{e^{(\beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \dots + \beta_{kj}x_{ki})}}{1 + \sum_{j=2}^J e^{(\beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \dots + \beta_{kj}x_{ki})}} \quad (3.16) \\ j = 2, \dots, J$$

Fitted values, or expected frequency, for each covariate pattern can be calculated by multiplying the estimated probabilities  $p_j$  by the total frequency of the covariate pattern.

Often it is easier to interpret the effects of explanatory factors in terms of odds ratios than the parameters  $\beta$ . For simplicity, consider a response variable with  $J$  categories and a binary explanatory variable  $x$  which denotes whether an 'exposure' factor is present ( $x=1$ ) or absent ( $x=0$ ). The odds ratio for exposure for response  $j$  ( $j = 2, \dots, J$ ) relative to the reference category  $j = 1$  is

$$OR_j = \frac{\left(\frac{p_{jk}}{p_{ja}}\right)}{\left(\frac{p_{1k}}{p_{1a}}\right)}$$

Where  $p_{jk}$  and  $p_{ja}$  denote the probabilities of response category  $j$  ( $j = 1, \dots, J$ ) according to whether exposure is present or absent, respectively.

Thus For the model

$$\log\left(\frac{p_j}{p_1}\right) = \beta_{0j} + \beta_{1j}x, j = 2, \dots, J \quad (3.17)$$

the log odds are

$$\log\left(\frac{p_{ja}}{p_{1a}}\right) = \beta_{0j} \quad (3.18)$$

when  $x = 0$ , indicating the exposure is absent, and

$$\log\left(\frac{p_{jk}}{p_{1k}}\right) = \beta_{0j} + \beta_{1j} \quad (3.19)$$

when  $x = 1$ , indicating the exposure is present.

Therefore the logarithm of the odds ratio can be written as

$$\begin{aligned}
 \log OR_j &= \log \left( \frac{p_{jk}}{p_{1k}} \right) - \log \left( \frac{p_{ja}}{p_{1a}} \right) \\
 &= \beta_{0j} + \beta_{1j} - \beta_{0j} \\
 &= \beta_{1j}
 \end{aligned} \tag{3.20}$$

and hence  $OR_j = \exp(\beta_{1j})$ . If  $\beta_{1j} = 0$  then  $OR_j = 1$  which corresponds to the exposure factor having no effect.

The 95% confidence limits for  $OR_j$  are given by

$$\exp\{\beta_{1j} \pm 1.96.s.e.(\beta_{1j})\} \tag{3.21}$$

Where  $s.e. (\beta_{1j})$  denotes the standard error of  $\beta_{1j}$ . Confidence intervals which do not include unity correspond to  $\beta$  value significantly different from zero.

For nominal logistic regression, the explanatory variables may be categorical or continuous. The choice of the reference category for the response variable will affect the parameter estimated  $\beta$  but not the estimated probabilities or fitted values.

### 3.2.1 Adopted Model of the study

In the study on place of maternal delivery, the response variable falls into three categories namely: home, public health facility, private health facility. It is worth noting that there is no natural ordering of the categories and the resulting model can be analyzed by using slightly modified methods called multinomial (polytomous) logistic regression.

The study has  $n$  independent observations with  $k=10$  explanatory variables. The qualitative response variable has  $J = 3$  categories. To construct the logits in the Multinomial case on the

categories, one category is considered to be the base level and all the logits are constructed relative to it.

In the study, any category had an equal chance of being taken as the base level. Making category  $j$ th as the base level in our description of the method since there is no ordering, it is apparent that any category may be labeled  $j^*$  ( arbitrarily chosen).

Let  $p_j$  denote the Multinomial probability of an observation falling in the  $j - th$  category. Thus the multinomial logistic regression model for finding the relationship between this probability and  $k$  explanatory variables is

$$\log \left( \frac{p_j(x_i)}{p_{j^*}(x_i)} \right) = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \dots + \beta_{kj}x_{ki} \quad j \neq j^*, i = 1, 2, \dots, n \quad (3.22)$$

since all the  $p$ 's add to unity, this reduces to

$$p_j(x_i) = \frac{e^{(\beta_{0j} + \sum \beta_{1j}x_{1i})}}{1 + \sum_{j=1}^{k-1} e^{(\beta_{0j} + \sum \beta_{1j}x_{1i})}} \quad (3.23)$$

$$\begin{aligned} p_{j^*}(x_i) &= 1 - \sum_{j \neq j^*} P_j(x_i) \\ &= \frac{1}{1 + \sum_{j \neq j^*} e^{(\beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \dots + \beta_{kj}x_{ki})}} \end{aligned} \quad (3.24)$$

As far as regression models for the analysis of categorical dependent variables with more than two response categories is concerned, several models were considered by generalizations of logistic regression analysis to polychotomous data that is, Multinomial logistic regression is the extension for the (binary) logistic regression when the categorical dependent outcome has more than two levels (unordered data with more than 2 categories) while ordinal logistic regression model uses ordered dependent outcomes with more than two categories.



Anchoring on the above discussions, the study to assess the factors that influences place of maternal delivery in the Country, Multinomial logistic regression model was thought to be more appropriate and was used to determine a parsimonious model to explain effects of various factors on place of maternal delivery in the country.

- (i). Specifying models in two parts: equations linking the response and explanatory variables, and the probability distribution of the response variable.
- (ii). Estimating parameters used in the models.
- (iii). Checking how well the models fit the actual data
- (iv). Making inferences; for example, calculating confidence intervals and testing hypotheses about the parameters.

The study examined the relationship between 10 main factors that were thought to influence place of maternal delivery in Kenya. Bivariate analysis with the Chi-square was used to describe and identify the significance of the explanatory variable (factors that influence) on place of delivery thereafter, backward selection was used to establish parsimonious model on place of maternal delivery.

### **Variables selection**

In the study, the place of maternal delivery in the country was the dependent variable, classified into three unordered categories as shown in table 3.2 below:

### **Dependent variable**

$y$  = place of delivery.

Table 3.2: Dependent (outcome) variable classification

Category	Descriptions
1	Home delivery
2	Public facility delivery
3	Private facility delivery

### Independent variables

All the variables identified as potentially important based on theoretical considerations were considered for inclusion in the model. Bivariate analysis was used to select the significant variables that were included in the final model.

$x_1$  = mother's education level,

$x_2$  = mother's age at birth

$x_3$  = number of children ever born

$x_4$  = region,

$x_5$  = ethnicity

$x_6$  = place of residence

$x_7$  = Wealthy Index

$x_8$  = Religion

$x_9$  = Mother's Occupation

$x_{10}$  = Partner's educational level of attainment

### 3.3 Measures of goodness of fit

Summary statistics for goodness of fit are analogous to those for binomial logistic regression namely,

i **Chi - square statistics**

$$Q = \sum_{i=1}^n r_i^2; \tag{3.25}$$

where  $r_i = \frac{O_i - E_i}{\sqrt{E_i}}$   $i = 1, 2, \dots, n$  are the Pearson  $\chi^2$  residuals, here  $O_i$  and  $E_i$  are the observed and expected frequencies for  $i = 1, \dots, n$  where  $n$  and  $J$  times are the number of distinct covariate patterns. The residuals can be used to assess the adequacy of the model.

ii. **Deviance**, defined in terms of the maximum values of the log-likelihood function for the fitted model,  $l(\beta)$ , and for the maxima model,  $l(\beta_{max})$ ,

$$D = 2[l(\beta_{max}) - l(\beta)]; \tag{3.26}$$

iii. **Likelihood ratio  $\chi^2$  statistic**, defined in terms of the maximum value of the log likelihood function for the minimal model,  $l(\beta_{min})$ , and  $l(\beta)$ ,

$$C = 2[l(\beta) - l(\beta_{min})]; \tag{3.27}$$

iv. **Pseudo  $R^2$**

$$Pseudo \ R^2 = \frac{l(\beta_{min}) - l(\beta)}{l(\beta_{min})} \tag{3.28}$$

If the model fits well then both  $Q$  and  $D$  ( $\chi^2$  statistic and Deviance respectively) have, asymptotically, the distribution  $(\chi^2_{(N-s)})$  where  $s$  is the number of parameters estimated.  $C$  has

the asymptotic distribution  $\chi^2 (s - (J - 1))$  because the minimal model will have one parameter for each logit.

### 3.4 Data Analysis

The data was mined from the Kenya Demographic and Health Survey 2008 data. To establish the underlying structure of the data, exploration and data analysis, SPSS version 10 statistical Package was used.

## Chapter 4

# MODEL APPLICATION AND RESULTS

The goal of objective of the study was to develop a parsimonious regression model that predict the category of outcome for individual cases using the parsimonious model.

### 4.1 Relationship of independent variables and dependent variables

There are two types of tests for individual independent variables: the likelihood ratio test evaluates the overall relationship between an independent variables and the dependent variable; the Wald test evaluates whether or not the independent variable is statistically significant in differentiating between the two groups in each of the embedded binary logistic comparisons.

The likelihood ratio test shows the contribution of each variable to the model. According to the likelihood ratio test, there is a statistically significant relationship between almost all independent variables and the dependent, with exception of religion ( $0.175 > 0.05$ ) and

Table 4.1: Likelihood Ratio test of explanatory variables

Effect	-2logLik of Reduced model,	$\chi^2$	df	sig
Intercept	7239	53.547	2	<0.0001
Mother's educational attainment	7313	126.84	2	<0.0001
Type of place of residence	7211	25.354	2	<0.0001
Region	7292	106.415	2	<0.0001
Religion	7189	3.486	2	0.175
Partner's education attainment	7254	67.932	2	<0.0001
Ethnicity	7225	38.794	2	<0.0001
Age at Birth	7200	14.341	2	<0.0001
wealth Index	7298	111.896	2	<0.0001
Mother's occupation	7189	2.991	2	0.224
No. of children ever born	8386.421	1200.617	2	<0.0001

Mother's occupation ( $0.224 < 0.05$ ) being statistically insignificant. This reduced the saturated model by the two insignificant variables i.e. religion and mother's occupation.

The reference category is private facility and the parameter is set to zero because it is redundant. Multinomial logistic regression models the relationship by comparing each of the categories defined by the dependent variables to the reference category. The interpretation for an independent variable focused on its ability to distinguish between pairs of groups and the contribution which it makes to change the odds of being in one dependent variable group rather than the other.

Tests for individual independent variables, the Wald test evaluates whether or not the independent variable is statistically significant in differentiating between the two groups in each of the embedded binary logistic comparisons. According to the parameter estimate, almost all independent variables plays a statistically significant role in distinguishing Home delivery

Table 4.2: Parameter estimates on explanatory variables

Place of delivery	Estimates	Std.Err	Wald	df	Sig.	Exp(B)
Home						
Intercept	3.304	0.474	48.547	1	0	
Mother's educ. attainment	-0.499	0.051	95.4	1	0	0.607
Type of place of residence	0.464	0.15	9.572	1	0.002	1.591
Region	0.269	0.03	83.285	1	0	1.309
Religion	-1.22E-02	0.009	1.726	1	0.189	0.988
Partner's education attainment	-0.374	0.048	61.057	1	0	0.688
Ethnicity	2.51E-03	0.003	0.756	1	0.384	1.003
Age at Birth	-0.324	0.119	7.476	1	0.006	0.723
wealth Index	-0.496	0.06	68.718	1	0	0.609
Mother's occupation	2.63E-03	0.022	0.014	1	0.906	1.003
No. of children ever born	0.105	0.03	12.375	1	0	1.111
Public facility						
Intercept	2.968	0.45	43.596	1	0	
Mother's educ. attainment	-0.174	0.046	14.035	1	0	0.84
Type of place of residence	-5.49E-02	0.136	0.163	1	0.686	0.947
Region	0.114	0.027	17.561	1	0	1.121
Religion	-9.37E-03	0.006	2.734	1	0.098	0.991
Partner's education attainment	-0.223	0.046	23.289	1	0	0.8
Ethnicity	-8.24E-03	0.003	7.943	1	0.005	0.992
Age at Birth	-6.78E-02	0.113	0.361	1	0.548	0.934
wealth Index	-0.219	0.059	13.584	1	0	0.804
Mother's occupation	2.39E-02	0.021	1.313	1	0.252	1.024
No. of children ever born	-1.57E-02	0.03	0.278	1	0.598	0.984

category from delivery in private facility which is a reference category. This holds for almost all independent variables, with exception of religion, ethnicity and mother's occupation variables which were insignificant. In addition, almost all independent variables were significant in distinguishing delivery in public facility from private facility which is a reference category. This holds for almost all independent variables, with exception of; type of place of residence, religion, ethnicity, number of child ever born and mother's occupation variables shows to be insignificant. If an independent variable has an overall relationship to the dependent variable, it might or might not be statistically significant in differentiating between pairs of groups defined by the dependent variable.

Multicollinearity in the multinomial logistic regression solution is detected by examining the standard errors for the  $\beta$  coefficients. A standard error larger than 2.0 indicates numerical problems. On study on place of maternal delivery, none of the independent variables in this analysis had a standard error larger than 2.0.

## 4.2 Adequacy of the Model

In the study of the place of maternal delivery, different summary measures of goodness of fit suggest the Model fits adequately. The presence of a relationship between the dependent

Table 4.3: Full Model fitting information

	AIC	BIC	-2 LogLK	$\chi^2$	df	P-Value
Intercept Only	9.564E3	9.577E3	9.560E3			
Final	7.230E3	7.376E3	7.186E3	2.374E3	20	<0.0001

variable and combination of independent variables is based on the statistical significance of the



Table 4.6: Case Processing Summary

	N	Marginal percentage
Home	3282	58.17%
Public facility	1782	31.58%
Private facility	578	10.24%
Valid	5642	
Missing	437	
Total	6079	

A more useful measure to assess the utility of a multinomial logistic regression model is classification accuracy, which compares predicted group membership based on the logistic model to the actual known group membership, which is the value for the dependent variables.

The estimate of by chance accuracy, is the proportion by chance accuracy rate, computed by summing the squared percentage of cases in each group, based in the case processing summary table 4.6.

$$\text{Chance accuracy rate} = (0.5817)^2 + (0.3158)^2 + (0.1024)^2 = 0.4486.$$

The benchmark that characterize a multinomial logistic regression model as useful is a 25% improvement over the rate of accuracy achievable by chance alone.

$$\text{The proportion by chance accuracy criteria is } (1.25)(44.86\%) = 56.075\%$$

### 4.3 Reduced Model

Table 4.7: Reduced model Fitting Information

	AIC	BIC	-2 LogLike	$\chi^2$	df	P-Value
Intercept	0.0091	0.0091	0.0091			
Final	6.744E3	6.864E3	6.708E3	2.369E3	16	<.0001

AIC of reduced model (6744) < AIC of the saturated (7230)

The reduced model is more adequate than the saturated model due to its smaller AKaike Information Criterion (AIC) compared to the saturated model AIC. The table on goodness

Table 4.8: Fit and Diagnostic of the reduced model

	$\chi^2$	df	P-value
Pearson	7765.240	5712	0.000
Deviance	5861.565	5712	0.082

of fit shows whether the model adequately fit the data. To check the goodness of fit,  $(sig) > 0.05$ . Since Deviance significance level is greater than 0.05 (i.e.  $0.082 > 0.05$ ) this shows the model adequately fit the data. The results indicate that there is association between the

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Table 4.9: Reduced Model Fitting Information Criteria and Likelihood Ratio Tests

Effects	AIC	BIC	-2 LogLike	$\chi^2$	df	p-value
Intercept	6.794E3	6.901E3	6.762E3	54.046	2	0.000
Region	6.854E3	6.960E3	6.822E3	114.011	2	0.000
Type of place of residence	6.766E3	6.872E3	6.734E3	25.510	2	.000
Ethnicity	6.784E3	6.890E3	6.752E3	43.918	2	.000
Mother's educ. attainment	6.870E3	6.976E3	6.838E3	129.822	2	.000
No. of children ever born	6.795E3	6.901E3	6.763E3	54.599	2	.000
Partner's educ. attainment	6.811E3	6.917E3	6.779E3	70.330	2	.000
wealth Index	6.852E3	6.958E3	6.820E3	111.594	2	.000
Age at Birth	6.756E3	6.862E3	6.724E3	15.473	2	.000

place of delivery and the following predictor variables: age at birth, ethnicity, type of place of residence, region, mother's education attainment, number of child ever born, partner's education attainment and wealth index.

If an independent variable has an overall relationship to the dependent variable, it might or might not be statistically significant in differentiating between pairs of groups defined by the dependent variable. Hence Wald test evaluation was applied in the study on place of delivery. The reference category is private facility and the parameter is set to zero because

Table 4.10: Parameter Estimates for the reduced model

	Estimate	Std.Err	Wald	df	P-Value	Exp( $\beta$ )
Home						
Intercept	3.269	0.468	48.804	1	.000	
Region	.273	.029	87.404	1	.000	1.314
Type of place of residence	.501	.148	11.455	1	.001	1.651
Ethnicity	.001	.003	.107	1	.744	1.001
Mother's educ. attainment	-.506	.051	99.587	1	.000	.603
No. of children ever born	.095	.030	10.272	1	.001	1.099
Partner's educ. attainment	-.379	.048	63.533	1	.000	.685
wealth Index	-.482	.059	65.948	1	.000	.618
Age at Birth	-.354	.118	9.063	1	.003	.702
Public facility						
Intercept	2.966	.444	44.570	1	.000	
Region	.112	.027	17.354	1	.000	1.119
Type of place of residence	-.005	.134	.001	1	.971	.995
Ethnicity	-.010	.003	14.354	1	.000	.990
Mother's educ. attainment	-.182	.046	15.677	1	.000	.834
No. of children ever born	-.023	.029	.597	1	.440	.978
Partner's educ. attainment	-.228	.046	24.502	1	.000	.796
wealth Index	-.200	.059	11.590	1	.001	.818
Age at Birth	-.097	.112	.747	1	.387	.908

it is redundant. Multinomial logistic regression models the relationship by comparing each of the categories defined by the dependent variables to the reference category.

Tests for individual independent variables, the Wald test evaluates whether or not the independent variable is statistically significant in differentiating between the two groups in each of the embedded binary logistic comparisons. According to the parameter Estimate, almost all independent variables plays a statistically significant role in distinguishing Home delivery from private facility delivery. This holds for almost all independent variables, with exception of ethnicity variables which were insignificant. ( $0.744 > 0.05$ )

In addition, independent variables that were significant in distinguishing delivery in public facility from private facility which is a reference category. Included; Region, ethnicity, mother's education attainment, wealth Index and partner's education attainment while type of place of residence, No. of child ever born and age at birth were insignificant. ( $0.971 > 0.05$   $0.440 > 0.05$   $0.387 > 0.05$  respectively. Therefore the adopted parsimonious model is

$$\log \left( \frac{p_j(x_i)}{p_3(x_i)} \right) = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \dots + \beta_{8j}x_{8i} \quad (4.1)$$

$$j \neq 3, i = 1, 2, \dots, n$$

where,  $k = 3, i = 1, 2, \dots, n$

becomes

$$\begin{aligned} = & \beta_{01} + \beta_{11}(\text{age}) + \beta_{21}(\text{ethnicity}) + \beta_{31}(\text{Type of residence}) + \beta_{41}(\text{region}) \\ & + \beta_{51}(\text{mother's educ.}) + \beta_{61}(\text{Child ever born}) + \beta_{71}(\text{partner's educ.}) \\ & + \beta_{81}(\text{wealth index}) \end{aligned} \quad (4.2)$$

will be reduced to:

- i. Reduced parsimonious model on home delivery while private facility delivery being reference

category

$$\log \left( \frac{p_j(x_i)}{p_3(x_i)} \right) = \beta_{01} + \beta_{11}(age) + \beta_{31}(Type\ of\ residence) + \beta_{41}(region) + \beta_{51}(mother's\ educ.) \\ + \beta_{61}(Child\ ever\ born) + \beta_{71}(partner's\ educ.) + \beta_{81}(wealth\ index) \quad (4.3)$$

substituting the explanatory variables including standard errors, the equation above reduces to:

$$\log \left( \frac{p_1(x_i)}{p_3(x_i)} \right) = (3.269 \pm 0.468) + (-0.354 \pm 0.118)age + (0.501 \pm 0.148)place\ of\ residence \\ + (0.273 \pm 0.029)region + (-0.506 \pm 0.0501)mother's\ educ. \\ + (0.095 \pm 0.030)(Child\ ever\ born) + (-0.379 \pm 0.0.48)partner's\ educ. \\ + (-0.482 \pm 0.059)wealth\ index \quad (4.4)$$

ii. Reduced parsimonious model on public facility delivery while private facility delivery being reference category

$$\log \left( \frac{p_2(x_i)}{p_3(x_i)} \right) = (2.966 \pm 0.444) + (-0.010 \pm 0.003)ethnicity + (0.112 \pm 0.027)region \\ + (-0.182 \pm 0.46)mother's\ educ. + (-0.228 \pm 0.46)partner's\ educ. \\ + (-0.200 \pm 0.059)wealth\ index \quad (4.5)$$

## Chapter 5

# CONCLUSION AND RECOMMENDATION

### 5.1 Conclusion

The study provides important insight into combination of factors influencing choice of delivery place with 58.17% of women delivery at home. The study also confirmed wide range of factors determining place of delivery which includes: socio economic, demographic status, cultural and reproductive behaviors. Specifically; ethnicity , region, mother's level of education attainment and wealth index important independent factors in determining the choice of delivery place.

### 5.2 Recommendation

- i To address the issue high level of home delivery for sustainable effects is to raise the level of women's education and in long run this will address the socio and culture behavior.



ii Provision of a sustainable and effective health care delivery system in the country.

iii There is need to determine the relationship of maternal mortality and neonatal to place of delivery.

# Appendix

\*\*\*\*\*Code for Full model\*\*\*\*\*

NOMREG pld (BASE=LAST ORDER=ASCENDING)

WITH V024 V025 V130 V131 V149 V201 V717 V729 V190 V212R

/CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)

LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)

/MODEL /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)

ENTRYMETHOD(LR) REMOVALMETHOD(LR) /INTERCEPT=INCLUDE

/PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.

\*\*\*\*\*Code for reduced model:\*\*\*\*\*

NOMREG pld (BASE=LAST ORDER=ASCENDING) WITH V024 V025 V131

V149 V201 V729 V190 V212R /CRITERIA CIN(95) DELTA(0) MXITER(100)

MXSTEP(5) CHKSEP(20) LCONVERGE(0)

PCONVERGE(0.000001) SINGULAR(0.00000001) /MODEL

/STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)

ENTRYMETHOD(LR) REMOVALMETHOD(LR)

/INTERCEPT=INCLUDE

/PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.

NOMREG

pld WITH v024 v025 v131 v149 v201 v729 v190 v212r

/CRITERIA = CIN(95) DELTA(0) MXITER(100) MXSTEP(5) LCONVERGE(0)

PCONVERGE(1.0E-6) SINGULAR(1.0E-8)

/MODEL

/INTERCEPT = INCLUDE

/PRINT = CLASSTABLE FIT CORB PARAMETER SUMMARY LRT .

NOMREG

pld BY v024 v025 v131 v149 v201 v729 v190 v212r

/CRITERIA = CIN(95) DELTA(0) MXITER(100) MXSTEP(5) LCONVERGE(0)

PCONVERGE(1.0E-6) SINGULAR(1.0E-8)

/MODEL

/INTERCEPT = INCLUDE

/PRINT = CLASSTABLE FIT CORB PARAMETER SUMMARY LRT .

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