Science Journal of Clinical Medicine
2022; 11(2): 45-56
http://www.sciencepublishinggroup.com/j/sjcm
doi: 10.11648/j.sjcm.20221102.12
ISSN: 2327-2724 (Print); ISSN: 2327-2732 (Online)

Determinants of the Number of Antenatal Care Visits During Pregnancy Period: The Case of Tigray Reginal State Region, Ethiopia

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To cite this article:

Sebwedin Surur Jemal, Nejat Mehammed Aseffa, Hagos Mekonen. Determinants of the Number of Antenatal Care Visits During Pregnancy Period: The Case of Tigray Reginal State Region, Ethiopia. *Science Journal of Clinical Medicine*. Vol. 11, No. 2, 2022, pp. 45-56. doi: 10.11648/j.sjcm.20221102.12

Received: April 8, 2022; **Accepted**: May 9, 2022; **Published**: May 19, 2022

Abstract: Antenatal care could be a preventive obstetric health care program geared toward optimizing maternal fetal outcome through regular monitoring of pregnancy. Whether or not world health organization (WHO) recommends a minimum of 4 antenatal care service (ANC) visits for normal pregnancy, existing evidence from developing countries including Ethiopia indicates there are few women who utilize it thanks to different reasons. 3711 pregnant women from Ethiopia demographic health survey (EDHS) of 2013 were used to analyze the determinants of the barriers in number of antenatal care service visits among pregnant women in Tigray regional state. The data were found to have no excess zeros since the number of zero visits less than non-zero visit of ANC and the variance (7.64) is much higher than its mean (2.46). This study provides numerical and graphical methods for checking the adequacy of the proportional odds regression model. Thus several count models such as Poisson, negative binomial (NB), zero inflated Poisson (ZIP), and zero inflated negative binomial (ZINB) regression models were fitted to select the model which best fits the data. Each of these models was compared using Statistical Package for the Social Sciences (SPSS ver. 16) by their likelihood ratio test (LR), Akaki and Bayesian information criteria and the model that have small Akaki and Bayesian information criteria's was good fit the data. Negative binomial regression model was found to be better fitted with data which is characterized by non-excess zeros and high variability in the non-zero outcome. Through the analysis, access to modern ANC visits during pregnancy was low in Tigray regional state. Rural residence, absence of ANC, NGO medical institution, absence of education, lack of governmental hospital or medical institution, poverty, and never union with partner was significantly related to not attending ANC visits. The finding of this study indicates that the minimum ANC service within the region is mostly because the results of direct effect with absence of health post available. Policies and plans must improve visit of ANC service of pregnant women by arising health post available in rural residence and creating awareness on ANC for the society.

Keywords: Antenatal Care, Pregnancy, Maternal Health, Family Planning, Motherhood

1. Introduction

Antenatal care could be a preventive obstetric health care program geared toward optimizing maternal fetal outcome through regular monitoring of pregnancy [1]. It is one of the "four pillars" of safe motherhood, as formulated by the Maternal Health and Safe Motherhood programmer, Division of Family Health, of the World Health Organization (WHO) [2]. The other three are safe delivery, essential obstetric care and family planning. That is why WHO [3] recommends a minimum of four ANC visits for women without complicated pregnancy in developing worlds which would include urine, blood tests and compulsory blood pressure measurement, assess maternal and fetal well-being, review and modify birth and emergency plans, advice, and counsel, give preventive measures and non- compulsory weight and height check at each visit [1]. The package was devised to ensure that women experience safe pregnancy and childbirth and have healthy infants, in other words, to prevent the dreaded outcomes: maternal death, and perinatal and infant death. The World Health Organization (WHO) has replaced the traditional approach to antenatal care, "a risk approach" with an updated approach to antenatal care that emphasizes quality over quantity of visits. The Maternal and Neonatal Health (MNH) programmer promotes a minimum of four antenatal care visits- ideally, at 16 weeks, 24-28 weeks, and 36 weeks for women with normal pregnancies [4]. Currently, seventy one percent of women worldwide receive any ANC; in developing countries, more than 95% of pregnant women have access to ANC. Almost majority of the births in developing countries still take place without a medically skilled attendant to aid the mother, and the ratio is even higher in developing nations. In sub-Saharan Africa, sixty nine percent of pregnant women have at least one ANC visit [5]. While different studies have looked at diverse risk factors for antenatal care (ANC) and delivery service utilization in the country. MoH of Ethiopia in 2007 reported that about 52% of Ethiopian women received one or more ANC visits, less than 17% received professionally assisted delivery care and 19% received postnatal care. Coverage for ANC is usually expressed as the proportion of women who have had at least one ANC visit during their pregnancy. As emphasized in the 2005 EDHS, access to modern ANC visits during pregnancy in rural areas remains very limited by international standards. According to EDHS, 2005, only 6% of women make their first ANC visit before the fourth month of pregnancy [1]. The median duration of pregnancy for the first ANC visit was 4.2 months for urban women compared with 6.0 for rural women. In urban areas where health services are physically accessible and ANC at public services are provided free of charge, only 32.4% of women seek the service before 16 weeks of gestation [6]. The report identified that 72% of mothers with at least secondary school education received ANC compared to 45% and 21% of mothers" with primary and no education respectively. Well-oriented women with pregnancy complications are also more likely to report four or more visits. In most countries, the greatest proportionate difference occurs between women following socioeconomic, demographic, health, and environmental related factors [7]. Information coming from community-based studies related to the Health Extension Programmed (HEP) in Tigray regional state is still very limited due to different factors. That is why this study is aimed to statistically analyze the determinants of the barriers in the number of antenatal care service visits among pregnant women in Tigray regional state. According to some studies, the negative binomial and Zero Inflated Poisson (ZIP) model appears to be superior when the event-stage distribution is positive and when there is moderate to moderately-high zero-inflation but not extreme zero–inflation. On such occasions, it is of interest to examine the applicability of the Zero Inflated models (ZIP, ZINB) and Hurdle models (Hurdle Poisson and Hurdle NB) in addition to Negative Binomial (NB) and Poisson regression models and compare their performances in terms of their goodness-of-fit statistics, AIC, BIC, likelihood ratio test and theoretical soundness. Generally, the study flow was contained a former explanation and a brief description of a number of ANC visits from general to the specific, literature review, statistical methodology and interpretation, and discussion of the result.

1.1. General Objectives of the Study

The general objective of the study was to assess antenatal care utilization and its associated factors among 15 to 49 years of age women.

1.2. Specific Objectives

In line with this general objective, the study would be attempts:

a) To identify socioeconomic and demographic factors which are associated with antenatal care service utilization.
b) To assess the level of antenatal care services among the residents of the study area.
c) To suggest strategies for improving use of ANC services.

2. Methods and Materials

2.1. Study Area and Data Source

This study was conducted in Tigray regional state. Tigray regional state is located in the Northern part of the country and has an estimated total population of 4.3 million of which 50.8% are females. The region is divided into seven zones and 47 weredas (districts), of which 35 are rural and 12 are urban.

The source of data for this study would be the 2011 Ethiopia Demographic and Health Survey which is obtained from Central Statistical Agency (CSA) [8]. It is the survey conducted in Ethiopia as part of the worldwide Demographic and Health Surveys project. The 2011 EDHS was designed to provide estimates for the health and demographic variables of interest for the following domains: Ethiopia as a whole; urban and rural areas (each as a separate domain); and 11 geographic administrative regions (9 regions and 2 city administrations), namely: Tigray, Afar, Amhara, Oromia, Somali, Benishangul-Gumuz, Southern Nations, Nationalities and Peoples (SNNP), Gambelia and Harari regional states and two city administrations, that is, Addis Ababa and Dire Dada. From those regions we take all women whose age is 15 to 49 years in Tigray regional state.

2.2. Research Design

An institution based cross-sectional study design was conducted.

2.3. The Dependent Variable

The dependent variable of the study was the number of antenatal care service visits during pregnancy period.

2.4. Independent Variables

Table 1. *Independent Variable.*

Explanatory variable	Categories
Type of place of residence	Urban=1, Rural=2
Highest educational level	No education=0, Primary=1, Secondary=2, Higher=3
Wealth index	Poorest=1, Poorer=2, Middle=3, Richer=4, Richest=5
Antenatal care: government hospital	No=0, Yes=1
Antenatal care: government health center	No=0, Yes=1
Antenatal care: NGO health facility	No=0, Yes=1
Current marital status	Never in union=0, Married=1, Living with partner=2, Widowed=3, Divorced=4, Separated=5

2.5. Methods of Data Analysis

2.5.1. Descriptive Analysis

In this study descriptive statistics is used to present data by using cross tabulations (frequency table), graphs and chart. In addition to that mean, variance and other measurement are also used in the study to explore the characteristics of respondent data and variable. It determines demographic and socio-economic characteristics of the respondents.

2.5.2. Inferential Statistics

In this problem we used count regression model to determine the association b/n the numbers of antenatal care service (visits) and with its demographic and socio-economic factors.

The usual tools from the basic statistical inference and GLM are valid.

Likelihood and Deviance Residual:

Individual test (Wald test).

2.5.3. Count Data Regression Models

An event count refers to the number of times an event occurs within a fixed interval often measured as a nonnegative, discrete, and constrained by a lower bound, which is typically zero. The lower bound constraint presents the greatest obstacle for analyzing count data when assuming a normal distribution for its skewness so that standard models, such as OLS regression are not appropriate. The Poisson regression is commonly used method to model count data formed under two principal assumptions: one is that events occur independently over given time and the other is that the conditional mean and variance are equal. However, the equality of the mean and variance rarely occurs; the variance may be either greater than the mean (over dispersion) or less than the mean (under dispersion) [9-12]. This indicates Poisson regression is not adequate. When there is preponderance of zeros, several models have been proposed for analyzing such data. Substantively, the choice between these models should be based solely on the data generating process. However, datasets can vary as a function of both the proportions of zeros and the distribution for the non-zeros. Sometimes over dispersion of a data may not be significant if the percentage of zeros is too high (might be 80% or more) and in such case ZIP and ZINB have nearly identical estimate of the parameters [Trends in Maternal Health in Ethiopia [9-12].

2.5.4. Poisson Regression Model

The number of ANC visits is a non-negative integer; most of the recent thinking in the field is the use Poisson regression model as a starting point. The pdf of standard Poisson regression model is given by:

$$p(y_i/\mu_i) = \frac{e^{-\mu_i}{\mu_i}^{y_i}}{y_i!}, \text{ i=0,1,2,...}$$

Where $p(y_i)$ is the probability of pregnant women i having$y_i$antenatal care service visits in nine (9) months of pregnancy period and μ_i is the Poisson parameter for pregnant women i, which is equal to pregnant women i 's expected number of antenatal care service visits in nine (9) months, $E(y_i)$. Poisson regression models are estimated by specifying the Poisson parameter μ_i (the expected number of antenatal care service visits) as a function of explanatory variables, the most common functional form being $\mu_i = \exp(\beta x_i)$, where x is a vector of explanatory variables and β is a vector of estimable parameters.

The log-likelihood function

$$E(y_i) = \mu_i = \exp({x_i}^T\beta).$$

To find the maximum likelihood function of, we define the likelihood function as follows:

$$L = l(\mu_i, \beta) = \prod_{i=1}^{n} \frac{e^{-\mu_i}{\mu_i}^{yi}}{yi!} = \prod_{i=1}^{n} \frac{e^{-e^{x_i^T\beta}}}{yi!}\left(e^{x_i^T\beta}\right)^{yi}$$

Taking log on both sides and we get:

$$\mathcal{L} = \log(l(\mu_i, \beta)) = \sum_{i=1}^{n} [y_i {x_i}^T\beta - e^{{x_i}^T\beta} - \log(y_i!)]$$

The first derivative of the log likelihood function is:

$$\frac{\partial L}{\partial \beta_j} = \sum_{i=1}^{n} \{y_i - \exp({x_i}^T\beta)\} X_{ij}$$

The second derivative of log likelihood function is given as follows:

$$\frac{\partial^2 L}{\partial \beta_j \partial \beta_k} = -\sum_{i=1}^{n} \exp(x_i{}^T\beta) x_{ij}\, x_{ik}\, \partial^2$$

Hence, the log-likelihood function of the Poisson regression model is nonlinear in β so that they can be obtained via using an iterative algorithm.

The most commonly used Iterative algorithms are either Newton-Raphson or Fisher scoring. In practice $\beta\hat{}$ is the solution of the estimating equations obtained by differentiating the log likelihood in terms of β and equating them to zero. Therefore, β will be obtained by maximizing using numerical iterative method [9].

Let x be n* (p+1) matrix of explanatory variables. The relationship between y_i and i^{th} row vector of x, x_i linked by

$$\log(\mu) = \eta_i = x_i{}^T\beta = \beta 0 + \beta 1x1 + \beta 2x2 + \ldots + \beta pxp,\ i = 1, 2 \ldots p$$

There are two principal assumptions in the Poisson model we need to regard: one is that events occur independently over time or exposure period, the other is that the conditional mean and variance are equal. The latter assumption is quite important. If it fails, the fitted model should be reconsidered.

2.5.5. Over Dispersion

In practice, it is often found that the data exhibit over dispersion. Generally, two sources of over dispersion are determined: heterogeneity of the population and excess of zeroes. The heterogeneity is observed when the population can be divided into many homogeneous subpopulations. The excess of zeroes is detected when the numbers of observed non zeroes exceed largely the number of zeroes produced by the fitted Poisson distribution.

When the variance of count data exceeds the mean, var $[y_i] > E[y_i]$, $i = 1, 2, 3 \ldots$ a feature of over dispersion will occur. When over dispersion occurs, the Poisson maximum likelihood estimator obtained will be incorrect [10].

Poisson model is a special case of negative binomial model. The negative binomial regression model reduces to the Poisson regression model when the over dispersion parameter $\delta \rightarrow 0$. To assess the adequacy of the negative binomial model over the Poisson regression model, we can test the hypothesis:

$H_o: \delta = 0$ (The Poisson model can be fitted well the data), versus.

$H_1: \delta > 0$ (The data would be better fitted by the negative binomial regression).

The likelihood-ratio test (LRT) is given by:

$$LRT = -2\log(\mathcal{L}/\mathcal{L}_o),$$

Where $\mathcal{L}_o$ and $\mathcal{L}$ are the maximum likelihood estimator of models under the null and alternative hypothesis, respectively. Under the null hypothesis LRT follows a chi-square distribution with degree of freedom one [10].

2.5.6. Negative Binomial Regression Model

The limitation of the Poisson regression model is that it does not work if the mean and variance of the outcome variable is not identical. Another alternative solution to overcome for this problem is negative binomial regression model. The negative binomial (or Poisson-gamma) model is an extension of the Poisson model to overcome possible over- dispersion in the data. It is obtained from the mixture of Poisson and Gamma distribution called Poisson-Gamma distribution. Negative binomial model allows extra variation, δ relative to the standard Poisson model. In this case the variance of negative binomial model is significantly greater than the mean.

A random variable Y_i, $i = 1, 2, 3 \ldots$ are called a negative binomial distributed count with parameter μ and δ the probability density function is expressed as follows:

$$f(y_{i;}\mu_{i,}\delta) = \frac{\Gamma\left(y_i + \frac{1}{\delta}\right)}{\Gamma\left(\frac{1}{\delta}\right) y_i} (1 + \delta\mu_i)^{-\frac{1}{\delta}} \left(1 + \frac{1}{\delta\mu_i}\right)^{-y_i}, i = 1,2,3, \ldots$$

With mean and variance, respectively, given by:

$$E(Y_i) = \mu_i = \exp(x_i{}^T\beta) \text{ and var } (Y_i) = \mu_i(1 + \delta\mu_i)$$

The term δ (read as delta) is called the dispersion parameter and assumed not to depend on a covariate. If the dispersion parameter $\delta \rightarrow 0$, then the negative binomial model reduces to the classical Poisson model. The likelihood function of the negative binomial model based on a sample of n independent observation is given by:

$$l(\mu_{i,}\delta; y_i) = \prod_{i=1}^{n} \left(\frac{\Gamma\left(y_i + \frac{1}{\delta}\right)}{\Gamma\left(\frac{1}{\delta}\right) y_i!} (1 + \delta\mu_i)^{-\frac{1}{\delta}} \left(1 + \frac{1}{\delta\mu_i}\right)^{-y_i} \right)$$

And the log-likelihood function is

$$L = l(\mu_{i,}\delta; y_i) = \sum_{i=1}^{n} \left\{ -\log(y_i!) + \log\left(\frac{\Gamma\left(y_i + \frac{1}{\delta}\right)}{\Gamma\left(\frac{1}{\delta}\right)} \right) - \frac{1}{\delta}\log(1 + \delta\mu_i) - y_i\log\left(1 + \frac{1}{\delta\mu_i}\right) \right\}$$

Where the following expression can be used to simplify the equation:

$$\left(\frac{\Gamma\left(y_i + \frac{1}{\delta}\right)}{y_i!\,\Gamma\left(\frac{1}{\delta}\right)} \right) = \prod_{i=1}^{n} \left(y_i + \frac{1}{\delta} - k\right) = -\delta^{y_i} \prod_{i=1}^{n} (\delta y_i - \delta k + 1)$$

Then

$$\mathcal{L} = \sum_{i=1}^{n} \{-\log(yi!) + \sum_{k=1}^{yi} (\log(\delta yi - \delta k + 1)) - (yi + 1/\delta)\log(1 + \delta\mu i) + yi\log(\mu i)\}$$

Where $\mu_i = \exp(x_i{}^T\beta)$

$$\mathcal{L} = \sum_{i=1}^{n}\{-\log(yi!) + \sum_{k=1}^{yi}(\log(\delta yi - \delta k + 1)) - (yi + 1/\delta)\log(1 + \delta\exp(xiT\beta)) + yixiT\beta\}$$

The likelihood equations to estimate β and δ are obtained by taking the partial derivatives of the log-likelihood function and setting them equal to zero. Thus, we obtain the first derivatives of the log-likelihood function L with respect to the underlying parameters are obtained as follows as:

$$\frac{\partial L}{\partial \beta} = \frac{\partial L}{\partial \mu}\frac{\partial \mu}{\partial \beta} = \sum_{i=1}^{n}\left[\frac{y_i - \mu_i}{1+\delta\mu_i}\right]x_i$$

$$\frac{\partial L}{\partial \beta} = \sum_{i=1}^{n}\left\{-\delta^{-2}\sum_{k=0}^{n-1}\frac{1}{\left(k+\frac{1}{\delta}\right)} + \delta^{-2}\log(1+\delta\mu_i) + \frac{y_i+\mu_i}{\delta(1+\delta\mu_i)}\right\}$$

The likelihood equation are non-linear in parameters β and δ. The above equations were solved simultaneously by using iterative algorithm. The iterative algorithm commonly used is either Newton–Raphson or Fisher Scoring [9-12].

2.5.7. Zero-Inflated Poisson Regression Model

ZIP model operates on the principle that the excess zero density that cannot be accommodated by a traditional count structure. In our case, the probability of an ANC visitation entity being in zero or non-zero states can be accounted by a splitting regime that models a woman who is not visited for ANC versus a woman who has visited for ANC during their pregnancy period determined by a binary logit or probit model [9-12]. ZIP model has two parts, i.e. the usual Poisson count model and the logit model which is used to predict excess zeros in the count dataset.

If the outcome variables y_i, i = 1, 2, 3, … have independent observations having a zero-inflated Poisson distribution, the zeros are assumed to arise in two ways corresponding to distinct underlying states. The first state occurs with probability ω_i and produces only zeros, while the other state occurs with probability 1 − and leads to a standard Poisson count with mean μ_i and hence a chance of further zeros. In general, the first state is called structural zeros and the other state from Poisson model are called sampling zeros [9-12]. This two-state process gives the following probability mass function (pmf):

$$p(Y_{i=}y_i) = \begin{cases} \omega_i + (1-\omega_i)e^{\mu i,} y_i = 0 \\ (1-\omega_i)\frac{e^{-\mu_i}\mu_i{}^{y_i}}{y_i!},\ y_{i=1,2,3,\ldots} \end{cases}$$

Where $0 \leq \omega_i \leq 1$, and μ_i. The parameter μ_i and ω_i depends on the covariates x_i and z_i,

Respectively. More specifically, we can write the model as follows:

$$\log(\mu_i) = x_i^T\beta,\ \log\left(\frac{\omega_i}{1-\omega_i}\right) = z_i^T Y$$

The mean and the variance of ZIP regression model respectively are:

$(y_i) = \mu(1-\omega_i)$, and $Var\ (y_i) = \mu_i(1-\omega_i)(1+\omega_i\mu_i)$.

The log-likelihood function, $\mathcal{L} = \ell(\mu_i, \omega_i; y_i)$ for ZIP model is given below:

$$L = \sum_{i=1}^{n}\{I(_{yi=0})\log[\omega_i + (1-\omega_i)\exp(-\mu_i)] + I_{(y_i>0)}[\log(1-\omega_i) - \mu_i + y_i\log(\mu_i) - \log(y_i!)]\}$$

With respect to the covariate x_i and z_i the log-likelihood function can be written as follows:

$$L = \ell\log(y_i \mid x_{i,}z_i) = \{I_{(y_{i=0})}\log[\exp(z_i{}^T\gamma) + \exp(-\exp(x_i{}^T\beta))] + I_{(yi>0)}[[y_i x_i{}^T\beta)] - \log(1+\exp(z_i{}^T\gamma))\}$$

2.5.8. Zero-Inflated Negative Binomial Regression Model

Zero-inflated negative binomial regression model is designed to model data with population heterogeneity which is caused by the occurrence of excess zeros and over dispersion due to unobserved heterogeneity [9, 10]. Many studies showed that ZINB model provides a better fit to the over dispersed count data when compared with ZIP model. We consider a zero-inflated negative binomial regression model in which the response variable y_i, i = 1, 2, 3,…n has the distribution [9-12].

$$P(Y_i = y_i) = \begin{cases} \{\omega_i + (1-\omega_i)(1+\delta\mu_i)^{\frac{-1}{\delta}}, yi = 0 \\ (1-\omega i)\left(\frac{\Gamma\left(y_i+\frac{1}{\delta}\right)}{y_i!\Gamma\left(\frac{1}{\delta}\right)}\right)(1+\delta\mu_i)^{-\frac{1}{\delta}}\left(1+\frac{1}{\delta\mu_i}\right)^{-y_i}, i = 1,2,3,\ldots \end{cases}$$

Where $\delta > 0$ is a dispersion parameter and is assumed not to depend on covariates.

The mean and the variance of the ZINB regression model are:

$E(y_i) = (1-\omega_i), (y_i) = (1-\omega_i)(1+\omega_i\mu_i + \delta\mu_i)$,

Where ωi = Inflation Probability.

The parameters μ_i and depend of covariates and z_i, respectively. We can write the model as

$$\log(\mu_i) = x_i^T\beta,\ \ \log\left(\frac{\omega_i}{1-\omega_i}\right) = z_i^T\gamma$$

$$\log(\mu_i) = x_i{}^T\beta,$$

$$\log(\mu_i) = \left(\frac{\omega_I}{1-\omega_i}\right)$$

3. Assessing Model Fit

3.1. Testing Hypotheses for the Significance Model Parameters

Overall Regression Test: does the entire set of explanatory or independent variables contribute significantly to the prediction of the response variable?

Hypothesis test

H_0: $\beta_1 = \beta_2 = \beta_3 = \cdots = \beta_k = 0$

Ha: Not all $\beta_j = 0$ for j = 1, 2, 3, 4, 5… L

This can be tested using the deviance test with L degrees of freedom. The deviance statistic [8] can be thought of as a measure of how well our model fits the data. The log likelihood ratio statistic (deviance) is given by:

$$\mathrm{D} = 2\left\{\sum \mathrm{yi}\log\left(\frac{\mathrm{yi}}{\lambda\mathrm{i}}\right) - \mathrm{yi} + \lambda\mathrm{i}\right\}$$

The null hypothesis is rejected if D>$\mathrm{X}^2(n), \alpha$.

Test for a Single Variable (Individual test): Let us assume that we now wish to test whether the addition of one particular explanatory variable of interest adds significantly to the prediction of the dependent over and above that achieved by other independent variables already present in the model. The null hypothesis for this test may be stated as "factor Xi does not have any value added to the prediction of the response given that other factors are already included in the model [9-12]. Symbolically:

H_0: $\beta_i = 0$

Ha: $\beta_i \neq 0$ for i = 1, 2… k

To test such a null hypothesis, we can use

$$t_i = \frac{\hat{\beta}_i}{se(\hat{\beta}_i)}$$

Where $\widehat{\beta}_i$ is the estimated regression coefficient and se ($\widehat{\beta}_i$) is the estimate of the standard error of $\widehat{\beta}_i$. This test statistic has the t-distribution with n-k-1 degree of freedom. High values of the test statistic indicate that the corresponding predictor variable is significant variable.

3.2. Likelihood Ratio Test (LRT)

The likelihood-Ratio chi-square (G^2) statistics is the test statistics commonly used for called log-likelihood ratio test, it is based on (-2*times log likelihood). Test of hypothesis the overall fit of the model.

H_0: The model is not a good fitting model (the predictors have not a significant effect).

H_1: The model is a good fitting model (the predictors have a significant effect).

The difference between 2LL for the best-fitting model and 2LL for the null hypothesis model (in which all the values are sent to zero) is distributed like assessing the overall fit of the logistic regression model. The likelihood ratio test, also chi-squared, with degrees of freedom equal to the number of predictors; this difference in the model chi-square.

$$-G^2 = -2\log\left(\frac{\iota_o}{\iota_1}\right) = -2[\log(\iota_o) - \log(\iota_1)]$$

3.3. Pearson Chi-square

A standard measure of goodness of fit for any model of y_i with mean $\hat{\mu}_i$ is the Pearson statistic:

$$\chi^2 = \sum_{i=1}^{n} \frac{\left(y_i - \hat{y}_i\right)^2}{\mathrm{var}(y_i)}$$

For an adequate model, the statistic has an asymptotic chi-squares distribution with n – k degrees of freedom, where n denotes the number of observations and k the number of unknown regression parameters in the model.

3.4. Akaki Information Criteria (AIC)

AIC is the most common means of identifying the model which fits well by comparing two or more than two models. It is trying to balance the goodness of fit against the complexity of the model It is similar as of the coefficient of multiple determination (R^2); however, it penalized by the number of parameter included in the model (i.e. the complexity of the model). Unlike the, the good model is the one which has the minimum AIC value. It is given by the following formula:

$$\mathrm{AIC}=-2\mathrm{L}+2\mathrm{K}$$

Where are the log likelihood of a model that will compare with the other models and is the number of parameter in the model including the intercept.

3.5. Bayesian Information Criteria (BIC)

Unlike the Akaki information criteria the Bayesian information matrix (BIC) takes in to account the size of the data under considered. It is given by:

$$\mathrm{BIC}=-2\mathrm{L}+\mathrm{K}\log(\mathrm{n})$$

Where L are the log likelihood of a model that will compare with the other models is the sample size of the data and k is the number of parameters in the model including the intercept.

For this study the AIC is preferred over the BIC as it is more stringent and has a stricter entry requirement than BIC for additional parameters when large datasets are used. This helps to resolve over-fitting of models where many additional parameters are added to increase the likelihood.

3.6. Parameter Estimation

Generally, Similar to the case of Logistic regression, the maximum likelihood estimators (MLEs) for (β_0, β_1 … etc.) are obtained by finding the values that maximizes log-likelihood. In general, there are no closed-form solutions, so the ML estimates are obtained by using iterative algorithms such as Newton-Raphson (NR), Iteratively re-weighted least squares (IRWLS), etc.

4. Result and Discussion

Data analysis was a critical study by which we extract information from data that we have collected. It was designed to provide with a strategy for investigating statistical questions. In addition, it provides with process for determining the structure of data should direct as to wards the proper inference procedure. Data was analyzed with reference to the purpose or objective of the study and analysis was done with reference to the research problem at hand or the hypothesis. Therefore we used both descriptive and inferential statistics for data analysis. In both descriptive and inferential we used SPSS software.

Descriptive Analysis:

The descriptive statistics given in table ANC shows that the number and percentage of ANC visits that the pregnant mothers in the sample have encountered in their nine months of pregnancy period. Based on this table 1593 (43%) of the pregnant mothers have not visited ANC service during their periods of pregnancy months, whereas 186 (5%) of them visited only once, 253 (6.8%) of them visited twice, 431 (11.6%) visited three times, 396 (10.7%) visited four times, 289 (7.8%) visited five, 220 (5.9%) visited six times, 152 (4.1%) visited seven times, and etc. These were again supported by figure below. Since there is large number of non zero ANC visit as compare to individual zero ANC visits, the histograms are highly picked at the very beginning (about the zero values). However large observations (i.e. large number of ANC visits) are less frequently observed. This leads to have a positively (or right) skewed distribution.

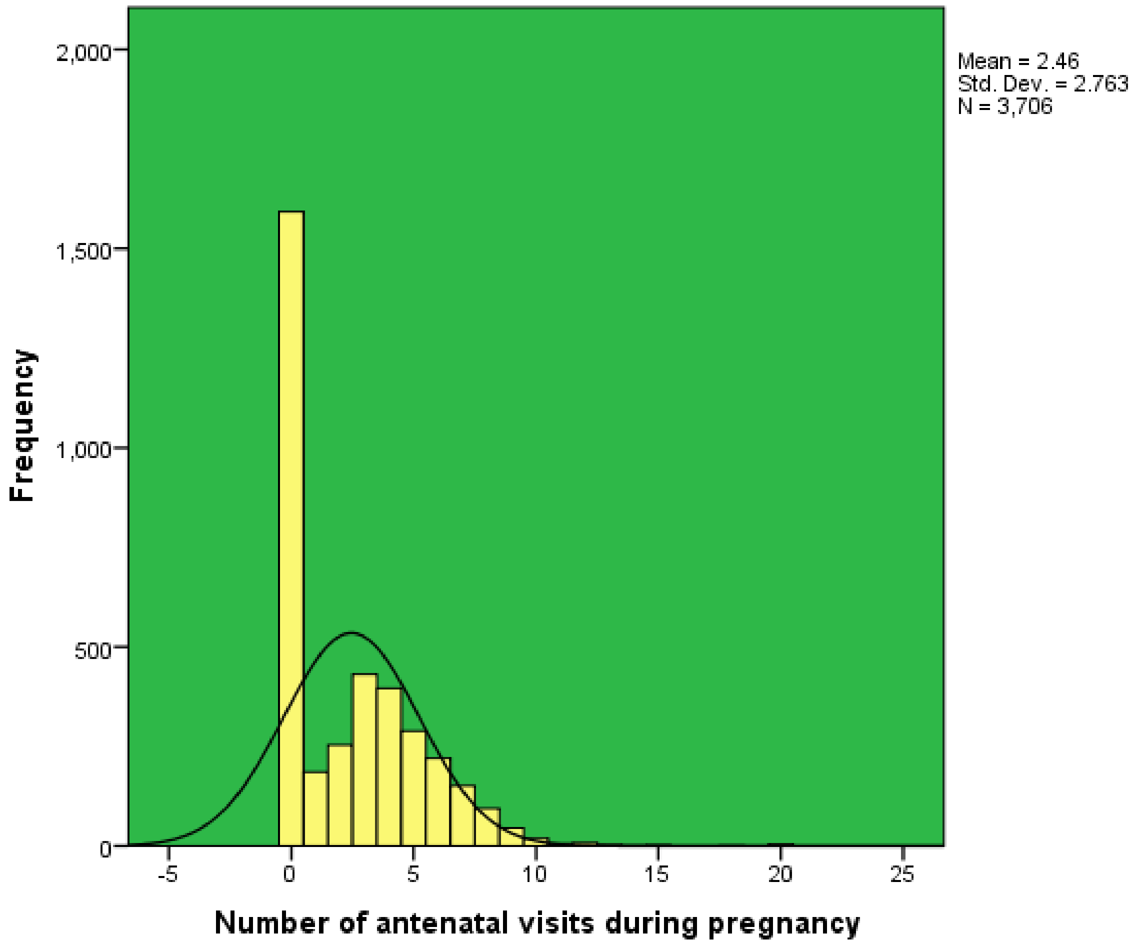

Figure 1. *Histogram of number of antenatal care visits during pregnancy.*

In this study the average numbers of antenatal care service visits of the total number of sample 3711 mothers is 2.46 and its variance is 7.63. The data have no excess of zero since the numbers of observed zeroes visits is less as compare to the overall non zero counts of ANC visits. in addition to that the variance of ANC data exceeds from its mean, var (y_i) =7.63>E (y_i)=2.46, i = 0,1, 2, 3 … therefore a feature of over dispersion would be occur on the data. The Poisson maximum likelihood estimator was incorrect. This was an indication that the data could be fitted better by count data models which takes into account no excess zeroes and over dispersion.

Table 2. *Descriptive statistic ANC data.*

Explanatory variable	Categories	ANC		Percentage
		USE	NOT USE	
Type of place of residence	Urban	113	632	20.1%
	Rural	1479	1478	79.8%
Highest educational level	No education	1291	1075	63.9%
	Primary	284	735	27.5%
	Secondary	16	202	5.9%
	Higher	2	101	2.8%
Wealth index	Poorest	779	373	31.1%
	Poorer	319	355	18.2%
	Middle	218	356	15.6%
	richer	173	316	13.2%
	Richest	104	713	22.0%
Antenatal care: government hospital	No	1010	1656	74.7%
	Yes	471	546	25.3%
Antenatal care: government health center	No	1298	1185	69.9%
	Yes	172	927	30.1%
Antenatal care: NGO health facility	No	893	1729	97.8%
	Yes	554	375	2.8%

The study was conducted on 3711 reproductive age (15-49) mothers inTigray regional state. From the total number of sample the percentage of wealth index of the pregnant mothers are 31.1% of them lives under condition of poorest, 18.2% poorer, 15.6% under middle and13.2% under richer conditions and etc. 20.1% of the respondent was lives in urban and 79.8% were lives in rural place of residence. The data identified that, 63.9% of mothers with no education compared to 27.5%, 5.9% and 2.8% of mothers‟ with primary, secondary and higher education respectively. The percentage of government health center those who give Antenatal care service for pregnant mothers in the sample were 55.1% have government health center. Based on the data 80.1%, 4.8%, 1.5%, 3.1% and 1.7% are Married, Living with partner, Widowed, Divorced and Separated respectively. Twenty five and point 3 (25.3% of respondent have government hospital which give ANC service. in addition to that 2.8% of those sample have NGO health facility that are functional ANC service.

4.1 Development of Count Data Regression Models

A first step in the model building process is to identify sets of independent variables that have the potential for being included in the linear component of a multivariable count data regression model. We start with fitting univariable Poisson regression model. The following table summarizes result obtained from SPSS ver.16 output of univariable Analysis.

Table 3. *Results of the Univariable Poisson Regression Model.*

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald Chi-Square	Sig.
Urban=1	1.003	.0214	.961	1.045	2205.501	.000
Rural=2	0^a	.	.	.	.	.
No education.=0	-1.367	.0414	-1.448	-1.286	1088.461	.000
Primary=1	-.740	.0422	-.823	-.657	308.215	.000
Secondary=2	-.174	.0479	-.268	-.080	13.209	.000
Higher=3	0^a	.	.	.	.	.
Poorest=1	-1.501	.0325	-1.564	-1.437	2134.829	.000
Poorer=2	-.978	.0326	-1.042	-.914	897.044	.000
Middle=3	-.691	.0311	-.752	-.630	492.804	.000
Richer=4	-.622	.0322	-.685	-.559	373.181	.000
Richest=5	0^a	.	.	.	.	.
No=0	.138	.0248	.089	.187	30.924	.000
Yes=1	0^a	.	.	.	.	.
No=0	-.572	.0211	-.613	-.531	733.946	.000
Yes=1	0^a	.	.	.	.	.
No=0	.551	.0280	.496	.606	387.773	.000
Yes=1	0^a	.	.	.	.	.
Never in union=0	-.966	.0825	-1.128	-.805	137.077	.000
Married=1	-.353	.0681	-.487	-.220	26.925	.000
Living with partner=2	.019	.0780	-.134	.172	.058	.809
Widowed=3	-.240	.1041	-.444	-.036	5.317	.021
Divorced=4	-.273	.0879	-.446	-.101	9.678	.002
Separated=5	0^a	.	.	.	.	.

From Table 3 we were identifying all covariates to be considered for the multivariable model. Inclusion of covariates would be based on a significant on the significance value (p-value) is less than or equal to 0.25.: Results of the Univariable indicate that the model is considered all the factors (covariate) in the multivariable parameter estimate since their p-value s are ≤ 0.25. The results are shown in table 3 above.

4.2. Determinants of Antenatal Care Service

At the initial stage, a Poisson model is fitted to identify the risk count antenatal care service. The fitted Poisson model is then tested for overdispersion. If so, the negative binomial model is an immediate solution to accommodate this overdispersion. Thus, in order to select an Appropriate model which fits the data well, different models were considered, namely the standard Poisson, and negative binomial model, zero inflated poison model, zero inflated negative binomial models.

4.3. Goodness of Fit and Test of Overdispersion

At this point we have a preliminary Poisson model and the next step is to assess its fit and adherence to key assumptions before we move to interpretation of the results obtained. We Start here first by checking the overall goodness of fit using deviance (likelihood ratio) Statistic. We then proceed to check for dispersion parameters in the Poisson model.

Goodness of fit of the fitted Poisson model was assessed using deviance-based chi-square test. Accordingly, the deviance-based chi-square test provided a chi-square value of 3670.696 with degrees of freedom 3507. (p=0.000) which would imply good fit for the model. The validity of Poisson regression analysis relies heavily on the assumption of equi-dispersion. The following table displays output of the Poisson and negative binomial regression fit statistics.

Table 4. *Test for Goodness of Fit between Poisson and Negative Binomial.*

Criteria	models	DF	Value	Value/DF	p-value
Deviance	Poisson	3507	8220	2.344	<0.0001
	Neg Bin	3507	3555	1.014	<0.0001
Scaled deviance	Poisson	3507	8220		
	Neg Bin	3507	3555		
Pearson Chi-Square	poisson	3507	8185	2.334	
	Neg Bin	3507	3209	0.915	
Scaled Pearson Chi-Square	poisson	3507	8185		
	Neg Bin	3507	8185		

In Poisson regression analyses, above table deviance and Pearson Chi-square goodness of fit statistics indicating over dispersion was obtained with value/df 8221 and 8.185E3 respectively. Since the Pearson chi-square statistic divided by the degrees-of-freedom is higher than one and the observed value of 2.344 is significantly different from one, with P-value <0.00001, then the mentioned goodness of statistics represents that there was an over dispersion in data set, indicating that there is over-dispersion and the Poisson model is inappropriate.. But the Deviance and Pearson chi-square goodness of fit statistics of 3.555E3 and 3.209E3 respectively in Negative Binomial regression is considerably an indication of not significant overdispersion exists; because the Pearson chi-square statistic divided by the degrees-of-freedom is approximately equal to one with the observed value of 0.915 and1.014 is significantly close to one as compare to 2.344. Therefore we fit a negative binomial regression model with the same explanatory variables. The value of deviance test statistic measured as twice the difference between likelihood of the Model without covariates and that of the full model is 3.555E3 with p-value <0.0001. Thus, the NB model with covariates is a better fit than Poisson model. The Pearson's chi-square test is used to assess the overall fit of the negative binomial regression model. The Results (chi square =3.209E3 with P-value <0.0001) show that the model is a good fit. The likelihood ratio test was used to compare the fit of the standard Poisson with Regression model. This statistic was found to be statistically significant, indicating that NB Regression model is a better fit to the data than the standard Poisson regression model (χ^2 (7) =1083.2, p-value =0.0000). Thus, the observed data are better explained by the negative Binomial than the Poisson model.

4.4. Methods Model Selections

Further as one can be seen from Table 5, the NB Regression model is a better fit than the Poisson model b/c overdisspersion in addition to this, the NB Regression model has smallest AIC (1.386E4) as well as BIC (1.397E4) values. Thus, it was used as the starting point for model selection. The detailed parameter estimates and standard errors for each model are provided in Table below. In this study we have Abstained different possible outcomes for the same ANC data by different count models. As it can be seen from the table of parameter estimate (Poisson& NB) almost categories of covariates included in the standard Poisson model are significantly associated with the number of ANC visits at 5% significance level. However in the case of the NB model only some of them are significant at 5%significance level. Therefore, the observed data are better explained by the negative binomial than the Poisson model.

Table 5. *Model Selection Criteria for the Regression Models Criteria.*

Criteria	Poisson regression model	negative binomial regression model
Logliklihood test	-7463	-6914
AIC	14960	13860
BIC	15070	13970

4.5. Model Effects and Statistical Significance of the Independent Variables

The Model Information: This confirms that the dependent variable is the "Number of ANC counts", the probability distribution is “negative binomial" and the link function is the natural logarithm (i.e., "Log").

H0: intercept only model (there is no relation between the explanatory variable and Number of ANC service Counts). Ha: at least one of the explanatory variables contributes for the Number of ANC service Counts value=0.00 less than α value(0.05)Then we reject the null hypothesis and indicate there is at least one parameter are different from zero. Based model effect table below shows that the tests of model effects. It evaluates each of the model variables with the appropriate degrees of freedom. The highest educational level of women, Type of place of residence, Wealth index, Antenatal care: government hospital, Antenatal care: government health center, Antenatal care: NGO health facility, Current marital status’ indicator variables. To assess the significance of these as a variable, we need to test these dummy (model) variables together in a minus one degree-of-freedom chi-square test from their categories’. If the p-value of this variable is greater than alpha value it is not statistically significant predictor of antenatal visits during pregnancy. The highest educational level of women is categorical with 4 levels. Thus it will appear in the model as 1 degree of freedom indicator variables. Since the p-value of highest educational level of women is less than alpha (0.05) values it is statistically significant predictor of ANC service. Type of place of residence is categorized with 2 levels. It will appear in the model as 1 degree of freedom indicator variable. Depending on the p-value Type of place of residence is statistically significant predictor of ANC service. Wealth index is categorized with five levels. It will appear in the model as one degree of freedom indicator variable. Since the p-value of Wealth index is less than alpha value it is statistically significant predictor of Number of antenatal visits during pregnancy. Antenatal care: government hospital is categorical with two levels. Thus, it will appear in the model as one degree-of-freedom indicator variables. Since the p-value of antenatal care: government hospital is less than alpha value it is statistically significant predictor on Number of antenatal visits during pregnancy. Antenatal care: government health center is categorical with two levels. Thus, it will appear in the model as one degree-of-freedom indicator variables. Since the p-value of Antenatal care government hospital is less than alpha value it is statistically significant predictor on Number of antenatal visits during pregnancy. In the same manner the Antenatal care: NGO health facility, Current marital status is statistically significant predictor on the Number of antenatal visits during pregnancy as the p-value is less than the alpha value.

Table 6. *Parameter Estimate for negative binomial regression model.*

Parameter	B	Std. Error	95% Wald C.I		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	Sig.	Exp (B)
Intercept	1.627	.2104	1.214	2.039	59.807	.000	5.075
Urban=1	.315	.0758	.167	.464	17.277	.000	1.369
Rural=2	0^a	.	.	.	.		
No education.=0	-.699	.1198	-.933	-.464	34.004	.000	0.498
Primary=1	-.337	.1186	-.570	-.105	8.093	.004	0.714
Secondary=2	-.051	.1311	-.308	.206	.149	.699	0.95
Higher=3	0^a	.	.	.	.		.
Poorest=1	-.886	.0834	-1.050	-.723	112.895	.000	0.413
Poorer=2	-.413	.0871	-.584	-.243	22.530	.000	0.662
Middle=3	-.166	.0865	-.335	.004	3.668	.055	0.887
Richer=4	-.163	.0858	-.331	.005	3.620	.057	0.849
Richest=5	0^a	.	.	.	.		.
No=0	.102	.0518	5.837E-5	.203	3.846	.050	1.107
Yes=1	0^a	.	.	.	.		.
No=0	-.413	.0475	-.506	-.320	75.479	.000	0.662
Yes=1	0^a	.	.	.	.		.
No=0	.198	.0544	.092	.305	13.278	.000	1.219
Yes=1	0^a	.	.	.	.		.
Never in union=0	-.293	.1709	-.628	.042	2.933	.087	0.746
Married=1	.051	.1519	-.246	.349	.114	.736	1.052
Living with partner=2	.227	.1754	-.117	.571	1.670	.196	1.254
Widowed=3	.332	.2251	-.109	.774	2.182	.140	1.393
Divorced=4	.047	.1899	-.325	.419	.062	.804	1.048
Separated=5	0^a	.	.	.	.		

$$Log(u(Xi))= 1.627+0.315\ X11\ -0.699\ X21 - 0.337\ X22 - 0.51\ X23 - 0.886\ X31 - 0.163\ X34 + 0.102\ X41 - 0.413\ X51 + 0.198\ X61 - 0.293\ X71 + 0.051\ X72 + 0.227\ X73$$

Where

X_{11}= Types of Place, X_{21}= no educated woman’s, X_{22}=primary level of education woman’s; X_{23}=secondary level of education woman’s, X_{31}=poorest, X_{32}=poorer, X_{33}=middle;

X_{34}=richer, X_{41}= have ANC: government hospital, X_{51}=

have Antenatal Care NGO health facility, X_{61}=have Antenatal care government health center, X_{71}=never in union, X_{72}=married;

X_{73}= living with partner, X_{74}= widowed, X_{75}= divorced.

The above model fitted with our ANC dataset, their coefficients have an important clinical and non-clinical meaning, and hence their interpretation is given below:

The output indicates that the odds ratio of number of ANC visits for mothers who were no formal education is 0.489, times the relative to mothers with higher level of education. The difference log of expected counts are expected to -0.699 lower for educations level of the woman's those who was no education compared to education level of the woman's whose completed tertiary level education, while holding the other variables constant in the model. And the odd of number of ANC visits for mothers who were primary level of education is 0.714, times the relative to mothers who were higher level of education. The difference logs of expected counts are expected to -0.337 lower for educations level of the woman's those who primary education compared to education level of the woman's whose completed tertiary level education, while holding the other variables constant in the model.

The odds ratio of number of ANC visits for mothers who were live in urban is 1.37 times relative to mothers who was live in rural urban place. The difference logs of expected counts are expected to 0.315 units higher for woman's who are live in urban area compared to for woman's who are live in rural place while holding the other variables constant in the model.

The odds ratio of number of ANC visits for mothers with poorest wealth index is 0.0413 times relative to mothers with richest wealth index. The difference logs of expected counts are expected to -0.886 lower for poorest mothers compared to richest mothers while holding the other variables constant in the model. The odds ratio of number of ANC visits for a mother with poorer wealth index is 0.66 times the relative to richest wealth index. The difference logs of expected counts are expected to -0.413 lower for poorer compared to richest individual while holding the other variables constant in the model.

The odds ratio of number of ANC visits for mothers with middle wealth index is 0.85 times relative to richest wealth index. The difference logs of expected counts are expected to -0.166 lower for middle compared to richest individual while holding the other variables constant in the model. Similarly the odds ratio of number of ANC visits for mothers with richer wealth index is 0.85 times relative to richest wealth index. The difference logs of expected counts are expected to -0.163 lower for richer compared to richest individual while holding the other variables constant in the model.

And the odds ratio of number of ANC visits for mothers who was no ANC government hospital is 1.11 times relative to mothers who were having ANC government hospital. The difference logs of expected counts are expected to 0.102 higher for no ANC government hospital compared to having ANC government hospital while holding the other variables constant in the model.

The odds ratio of number of ANC visits for mothers who was never in union is 0.75 times relative mothers who were separated. The difference logs of expected counts are expected to - .293 lower for never in union compared to no longer living with partner (separated) while holding the other variables constant in the model. The odds ratio of number of ANC visits for mothers who was married is 1.05 times relative to mothers who were separated. The difference logs of expected counts are expected to 0.051 higher for married compared to no longer living with partner (separated) while holding the other variables constant in the model. The odds ratio of number of ANC visits for mothers who was living with partner is 1.254 times relative to mothers who were separated. The difference logs of expected counts are expected to 0.227 higher for living with partner compared to no longer living with partner (separated) while holding the other variables constant in the model.

The odds ratio of number of ANC visits for mothers who was widowed is 1.393 times relative to mothers who were separated. The difference logs of expected counts are expected to 0.332 higher for widowed compared to no longer living with partner (separated) while holding the other variables constant in the model.

The odds ratio of number of ANC visits for mothers who was divorced is 1.393 times relative to mothers who were separated. The difference logs of expected counts are expected to 0.047 higher for divorced compared to no longer living with partner (separated) while holding the other variables constant in the model.

4.6. Discussion

The following variables: place of residence, wealth index, Highest educational level And antenatal care: government hospital, Antenatal care: government health center, Antenatal care: NGO health facility and Current marital status has been identified as having statistical significant association with number of antenatal care visit so that this helps policy makers further planning.

Gurmessa's report [13] determined that having monthly family income of 500 Ethiopian Birr and above (OR=1.53) were positively associated with antenatal care service utilization. This agrees with our finding that rich and middle incomer women were more likely to attend ANC visits.

A report from Samre Saharti district in Tigray region of Ethiopia found similar from our finding that being separate with her husband or partner have significant association with ANC utilization [14].

This result was the same with the study conducted in Metekel zone which confirms that education status of secondary school and above had positive effect on ANC visits than non-educated ones, and similar in our case. The finding of this studies nearly the same with that of EDHS 2005 which showed almost twenty two percent of attendance of ANC in the rural areas of Ethiopia [8, 12]. This could be attributed to the fact that DHS covered more remote areas where distance from health institution could be a major predictor of ANC utilization [14-17].

5. Conclusions

The reduced model with the logit link become the better model based on the screening Criteria, the validity model assumption, the fitting statistics (Person's chi-square and Deviance) and the stability of parameter estimation. The study examined the socio-demographic of determinants of number of ANC in Tigray region. Results of proportional odds model shows that socio-demographic variables are statistically significant determinant of number of ANC outcome.

The results of the study show that several factors such as level of education, types of residence, wealth index, marital status and health post available of the region were statistically significant effect on the outcome of ANC.

In addition, it is worth nothing that majority of the mothers did not receive minimum number of antenatal care visits recommended by the WHO. The findings of the study show that different factors such as mother education, Wealth index, availability and accessibility of health post, and Current marital status were statistically significant effect on the outcome of ANC. Rural residence, absence of ANC NGO health facility, absence of education, lack of governmental hospital or health center, poverty, and never union with partner was significantly associated with not attending ANC visits. The graphs of outlier influential and residuals points confirmed that observations are best fitted by the model and stability of parameter estimates is fulfilled. The proportional odds model assumption was also checked numerically using score test and graphically plots of cumulative logits as parallel linear function of covariates. The results justified that the assumption was fulfilled.

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