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Determinants of Under-Five Age Mortality in Adigrat Town

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***Abstract*: This project is done based on the major determinants of under-five age mortality in Adigrat town. The main aim of this study was to identify the main factors that affect the child death. The data collection was done through primary data sources that obtained from the respondents by interviewing the women age between 15-49 aged and the town administrative office. Simple random sampling method is used for sample selection and sample size determination in this study. The result by poison regression model confirms that there is an association between under-five age mortality and father's education, family income, mother's age at first birth of child, health status of mother, breastfeeding status and child vaccination adaptation. It also indicates that children born from working mothers have higher risk of mortality than non-working mothers.**

***Key words*: Children, Determinants, Mortality, Poisson regression, under-five**

I. INTRODUCTION

Under-five age mortality is a leading indicator of child health and overall development of a nation, as it reflects the social, economic and environmental conditions in which children live including their healthcare [1].Worldwide, 5.9 million children below five years age died in 2015. The risk of a child dying before completing five years of age is still the highest in the World Health Organization (WHO) African countries (81 per 1000 live births), about 7 times higher than in the WHO European region (11 per 1000 live births). Sub-Saharan Africa continues to confront significant challenges, as the region with the highest child mortality rates in the world: 98 deaths per 1000 live births in 2012. All 16 countries with an under-five age mortality rate above 100 deaths per 1000 live births are in sub-Saharan Africa [3].The U5MR has been selected as one of the most important indicator of child mortality because it presents the best concept of capturing mortality risks during the susceptible years of child hood(2). Because of the importance of reducing U5MR for societies, it is one of the United Nation 2015 Millennium Development Goals aims (3). The main objective of this study was to investigate the determinants of under-five age mortality in Adigrat town.

II. METHODOLOGY

The study population for this study was death of children in Adigrat town which is under-five age mortality.

Study design

The study was conducted through both qualitative and quantitative research techniques. The questionnaires was included both open and close ended questions.

Sampling Technique

The data was collected by simple random sampling method from the samples selected from the population of the study.

Sample Size Determination

The target population was the women aged between15-49 who gave birth live in Adigrat town at the study period. The sample size of the study was selected by calculation from the total number of women in the study area. The total number of women is obtained from the town administration office. The sample size was calculated by the help of sample size determination formula.

Then the sample size is:

$$n_0 = \frac{Z^2_{\alpha/2}pq}{d^2} \text{ take n } = n_o \text{ if } \frac{n_0}{N} < 0.05 \text{ and take n } = \frac{n_0}{1+\frac{n_0}{N}}$$

if $\frac{n_0}{N} > 0.05$

$$n_0 = \frac{Z^2_{\alpha/2}pq}{d^2} = \frac{3.84*0.5(1-0.5)}{(0.1)^2} = 96$$

$\frac{n_0}{N} = \frac{96}{4397} = 0.0218$, since $\frac{n_0}{N} < 0.05$ so the sample size of this study was 96.

Study Variables

The dependent variable of the study is the number of count children under-five age mortality. The determinants of childhood mortality such as Mother's education, Father's education, Marital status, Family size, Mother's age at first birth of child, Place of delivery, Family income, Health status of mothers, Parental care, Type of birth, Breast feeding status and Child vaccination adaptation were independent variables of the study.

Methods of Data Analysis

Under-five mortality rate is referred as the number of deaths of child under five year of age to the number of live births. Descriptive statistics and inferential statistics like as poison regression and chi-square test are used. In this study, the variable of interest is a count variable. For count data, the standard framework for explaining the relationship between the outcome variable and a set of explanatory variables includes the Poisson and negative binomial regression models. The two most popular models for count data are the Poisson model and the negative binomial model. The Poisson distribution should have the same mean and variance and the negative binomial regression model can be used instead of Poisson regression model when the data under consideration is over dispersed. A limitation of the Poisson distribution is the equality of its mean and variance. When the variance is larger than the mean negative binomial regression model can be applied. This is termed over-dispersion, and its presence renders the assumption of a Poisson distribution for the error process untenable. If the dispersion parameter (α) approaches to zero, it is appropriate to fit a Poisson regression model. The negative binomial (NB) distribution is a two-parameter distribution. For positive integer n, it is the distribution of the number of failures that occur in a sequence of trials before n successes have occurred, where the probability of success in each trial is p. By over-dispersion, we mean that the variance of the outcome variable is larger than the expected value of the outcome variable. Zero-inflated means that there is excess number of zeros in the outcome variables. The ZINB model is useful for analysis of over-dispersed count data with an excess of zeros. In practice, even after accounting for zero-inflation, the non-zero part of the count distribution is often over-dispersed. In this case, Greene .W.H (1994), described an extended version of the negative binomial model for excess zero count data, the zero-inflated negative binomial (ZINB) regression model, which may be more appropriate than the ZIP model. The data analysis was done using SPSS 20, STATA, and SAS statistical (software) packages.

Chi-Square Test

A variety of statistical test are available for analyzing of data. using chi-square is one of the most appropriate way to use with categorical variables of interest expected value is the member of subjects in the sample in which to observe data hence the test applied when the research have two or more categorical variables hence the quantitative data use.

Poisson Regression Model

Poisson regression is used to predict a dependent variable that consists of "count data" given one or more independent variables. Poisson regression models provide a standard framework for the analysis of count data. Let Yi represent counts of events occurring in a given time or exposure periods with rate μi. Yi are Poisson random variables which the p.m.f. is characterized by

$Pr\{Yi=yi\}=e^{-\mu i}\mu i^{yi}/yi, \mu i>0,\ i=1,2,\ldots\ldots\ldots n$ and yi = 0, 1, 2,

The mean and variance of this distribution can be shown to be

$E(Y) = var(Y) = \mu$.

Since the mean is equal to the variance, any factor that affects one will also affect the other. Thus, the usual assumption of homoscedasticity would not be appropriate for Poisson data.

Assumptions of Poisson regression model.

We can use the Poisson regression the following assumptions are not violated dependent variable consists of count data, the distribution of counts follow a Poisson distribution and the mean and variance of the model are identical.

Parameter Estimation for Poisson regression model

Maximum Likelihood Estimation

The likelihood function for n independent Poisson observations is a product of probabilities distribution function. Taking logs and ignoring a constant involving log(yi) we find that the log-likelihood function is

$\log L(\beta) = X\{yi \log(\mu i) - \mu i\}$,

where, μi depends on the covariates xi and a vector of p parameters β.

The method of maximum likelihood used to estimate the parameters from the linear transformed regression model $x_i'\beta.\hat{\beta}$ be the final estimate of the model parameters. $E(\hat{\beta})=\beta$ and $var(\hat{\beta})=(x'vx)^{-1}$ where the matrix V is an n×n diagonal matrix containing the estimated variance of each observation on the main diagonal; that is the i^{th} diagonal element of v is $v_{ii}= ni\hat{\pi}(1-\hat{\pi})$ the estimated value of the linear predictor is $\hat{\eta}i=xi'\hat{\beta}$, and the fitted value of the regression model.

$$\hat{y}i=\hat{\pi}i= \frac{\exp(\hat{\eta} i)}{1+\exp(\hat{\eta} i)}=\frac{\exp(xi'\hat{\beta})}{1+\exp(xi'\hat{\beta})}=\frac{1}{1+\exp(-xi'\hat{\beta})}$$

(Douglas. Montgomery, 2006)

Odd ratio $(\hat{\theta}_R) = \frac{oddsxi+1}{oddsxi} = \exp(\hat{\beta}_1)$ to use single explanatory variables, so that the fitted value of the linear predictor at a particular value of x, say x_i is

$\hat{\eta}(x_{i+1})=\hat{\beta}_0+\hat{\beta}_1(x_{i+1})$ where: $\hat{\eta}(xi)$ is just the log-odds when the regression is equal to x_i. $\hat{\eta}(x_{i+1})$ is just the log-odds when the regression is equal to x_{i+1}

The likelihood of a set of parameter values ,β given outcomes x is equal to the probablity of those observed outcomes given these parameter values, that is $f(\beta/x)=p(x/\beta)$. The likelihood function the joint probablity (density) function of observed random variable but its veiwed as the function of the parameter given the realized random variable.

$$L(x/x_{1,\ldots,}x_{j}) = \prod_{i=1}^{n} e^{-\lambda}\frac{\lambda^{xi}}{xi!} = \frac{1}{\prod_{i=1}^{n} xi!}e^{-n\lambda}\lambda^{\Sigma xi}$$

Where $X_i'=(1,x_{i1},x_{i2},\ldots,x_{ik})$ are explanatory variables and, $\beta' = (\beta1, \beta2, \beta3, \ldots, \beta k)$ are the regression coefficients .

$\pi(X_i)$Denotes the "success" probability at value X_i and given by:-

$$\pi(X_i) = \frac{1}{1 + \exp(X_i'\beta)}$$

Overall Significance the poison Regression Model

To test the overall significance for the poison regression model by the chi-square test of goodness of fit, Chi-square test.

Hypothesis test;

H0=the model is good fit

H1=not H0

Decision; reject H0 in favor of H1 if p-value is less than α

Test for individual predictors

Let β denote an arbitrary parameter. Consider a significance test of $H0$:β0=0. The simplest test statistic uses the large-sample normality of the ML estimator , let SE(β) denote the standard error of β , evaluated by substituting the ML estimate for the unknown parameter in the expression for the true standard error.

When $H0$ is true, the test statistics

Z = β–β0/SE(β)

has approximately a standard normal distribution. Equivalently, z^2 has approximately a chi-squared distribution with df = 1. This type of statistic, which uses the standard error evaluated at the ML estimate, is called a Wald statistic.

The Wald statistic is

$Z^2=(\beta-\beta 0)^2/SE(\beta))2$

Under H0 true, Z^2 is a chi-square distribution with 1 degree of freedom. Wald statistics are for small samples. Likelihood-ratio tests are generally considered to be superior (Agresti, 2007).

AIC and BIC

AIC and BIC are goodness of criteria used for model selection. Akakie information criteria (Akakie, 1973) or Bayesians information criteria (Raftery, 1986) abbreviated by AIC and BIC, respectively.

AIC = -2 log likelihood + 2k

BIC = -2 log likelihood +k ln(n)

where,

k = number of parameters and n = number of observations.

III. RESULT AND DESICCATION

Descriptive Analysis

Information on the number of deaths of under-five children obtained from a total of 4,397 women in the Adigrat town was studied. Tables showed the frequency and percentage distribution of the number of under-5 deaths in Adigrat town based on information from 4,397 women15-49 aged.

This section present a discussion of few variables included in the study and a brief summarized table that include all explanatory variables.

All the required information was gathered from 96 Mothers in age 15-49 years in Adigrat town to investigate the factor that affect the numbers of count under-five mortality. The frequency procedure is one of the descriptive analysis, which is used to display the frequency of the categorical variable and it provides statistic and graphical displays that are useful for describing many type of variable. 54.1% of the mothers have no educated, (21.6%) have primary level, and (10.8%) are secondary and higher of education. 45% of the fathers have no educated, (27.9%) have primary level, and (13.5%) are secondary and higher of father's education.

Table 1 number of count under- five mortality rate

		Frequency	Percent	Valid %	Cum.%
Valid	0	44	39.6	45.8	45.8
	1	32	28.8	33.3	79.2
	2	15	13.5	15.6	94.8
	3	5	4.5	5.2	100.0
	Total	96	86.5	100.0	
Missing	System	15	13.5		
Total		111	100.0		

The result of the above table indicate that most of the respondents (46.8%) at least have one died child.

Model and variable information in the poison regression model

The above result confirms that the dependent variable is the "Number of count under-five mortality", the probability distribution is "Poisson" and the link function is the natural logarithm (i.e., "Log"). If we are running a Poisson regression on our own data the name of the dependent variable are number of count under-five mortality, and the probability distribution and link function are expressed.

The mean is 0.80 and the variance is 0.7921 (0.890^2), which is a ratio of 0.7921 ÷ 0.80 = 0.990. A Poisson distribution assumes a ratio of 1 (i.e., the mean and variance are equal). Therefore, we can see that before we add in any explanatory variables there is a small amount of under dispersion. But the ratio is approximate to one. However, we need to check this assumption when all the independent variables have been added to the Poisson regression.

Table 2

	Value	df	Value/df
Deviance	34.508	73	.473
Scaled Deviance	34.508	73	
Pearson Chi-Square	35.191	73	.482
Scaled Pearson Chi-Square	35.191	73	
Log Like lihood[a]	-76.336		
Akanke's Information Criterion (AIC)	198.673		
Finite Sample Corrected AIC (AICC)	214.006		
Bayesian Information Criterion (BIC)	257.653		
Consistent AIC (CAIC)	280.653		

Dependent Variable: number of count under- five mortality rate

Model: (Intercept), ME, FE, MS, FS, MAC, PD, HSM, PC, TBS, BS, CVA, SX, FI

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

The Goodness of Fit table provides many measures that can be used to assess how well the model fits. However, we will concentrate on the value in the "Value/df" column for the "Pearson Chi-Square" row, which is 0.482. this is indicates a little pit under dispersion.

Table 3 Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
74.003	22	.000

Dependent Variable: number of count under- five mortality rate

Model: (Intercept), ME, FE, MS, FS, MAC, PD, HSM, PC, TBS, BS, CVA, SX, FI

It is a likelihood ratio test of whether all the independent variables collectively improve the model over the intercept-only model (i.e., with no independent variables added). Having all the independent variables in our model we have a *p*-value of .000 (i.e., *p* = .000), indicating a statistically significant overall model, as shown above in the "Sig." column. Now that you know that the addition of all the independent variables generates a statistically significant of the model, you will want to know which specific independent variables are statistically significant in the model we can see in the below tables.

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-4.032	1.1941	-6.372	-1.691	11.400	1	.001
[ME=0]	.977	.4708	.054	1.900	4.305	1	.038
[ME=1]	1.105	.4899	.145	2.065	5.090	1	.024
[ME=2]	0[a]	.	.	.	.	.	.
[FE=0]	-.810	.2921	-1.382	-.237	7.683	1	.006
[FE=1]	-.190	.2794	-.737	.358	.461	1	.497
[FE=2]	0[a]	.	.	.	.	.	.
[MS=0]	.297	.3150	-.321	.914	.888	1	.346
[MS=1]	.687	.3492	.003	1.371	3.872	1	.049
[MS=2]	.134	.4424	-.733	1.001	.092	1	.762
[MS=3]	0[a]	.	.	.	.	.	.
[FS=0]	-.153	.3727	-.883	.578	.167	1	.682
[FS=1]	-.267	.3802	-1.013	.478	.495	1	.482
[FS=2]	0[a]	.	.	.	.	.	.
[MAC=0]	-.082	.1980	-.470	.306	.172	1	.679
[MAC=1]	.236	.3234	-.397	.870	.534	1	.465
[MAC=2]	0[a]	.	.	.	.	.	.
[PD=0]	1.254	.2442	.776	1.733	26.376	1	.000
[PD=1]	0[a]	.	.	.	.	.	.
[HSM=0]	.291	.3041	-.305	.887	.914	1	.339
[HSM=1]	0[a]	.	.	.	.	.	.
[PC=0]	-.020	.2072	-.426	.386	.009	1	.923

[PC=1]	0[a]	.	.	.	.	.	.
[TBS=0]	-.064	.3249	-.700	.573	.038	1	.845
[TBS=1]	0[a]	.	.	.	.	.	.
[BS=0]	1.370	.7348	-.070	2.810	3.477	1	.062
[BS=1]	1.529	.7416	.076	2.983	4.252	1	.039
[BS=2]	0[a]	.	.	.	.	.	.
[CVA=0]	-.580	.4385	-1.439	.280	1.747	1	.186
[CVA=1]	-.930	.4474	-1.807	-.054	4.325	1	.038
[CVA=2]	0[a]	.	.	.	.	.	.
[SX=0]	.424	.2114	.010	.839	4.029	1	.045
[SX=1]	0[a]	.	.	.	.	.	.
[FI=0]	1.308	.4434	.439	2.177	8.697	1	.003
[FI=1]	.783	.4596	-.118	1.683	2.900	1	.089
[FI=2]	0[a]	.	.	.	.	.	.
(Scale)	.473[b]						

Dependent Variable: number of count under- five moratality rate
Model: (Intercept), ME, FE, MS, FS, MAC, PD, HSM, PC, TBS, BS, CVA, SX, FI

a. Set to zero because this parameter is redundant.

b. Computed based on the deviance.

The intercept (0.001) of the Poisson regression estimate when all variables in the model are evaluated at .001. For the variables mother education, with the log of the expected count for under-five mortality is -4.032 units. The indicator variable [ME=0] is the expected difference in log count between ME 0 and the reference ME [ME=2]. Compared to level 2 of ME, the expected log count for level 0 of ME increases by about 0.977. The indicator variable [ME=1] is the expected difference in log count between ME 1 and the reference ME. Compared to level 2 of ME, the expected log count for level 1 of ME increases by about 1.105.and the others like this….. The table displays the statistical significance of each of the independent variables in the "Sig." column

P-value

The p-values test whether or not an observed relationship is statistically significant.

This p-value tells if there is a significant association between at least one predictor and the response by testing whether all slopes are equal to zero. Compare this p-value to your α-level. If the p-value is less than or equal to the α-level you have selected, the association is significant. A commonly used α-level is 0.05. If the p-value is less than or equal to the α-level, then the association is significant, And conclude that at least one predictor is significantly associated with the response. If the p-value is greater than the α-level, then conclude that there is no significant association and the interpretation ends.

There is not usually any interest in the model intercept. However, we can see the independent variables that the family size , mother's age at first birth of child, ….were not statistically significant (p = .682, .123….respectively) are greater than the α values for 95%. but the variables mother's education, father's education…….. were statistically significant (p = .038,……respectively) are less than the α value for 95%. This table is mostly useful for categorical independent variables because it is the only table that considers the parameter estimates.

IV. CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The purpose of this paper was to examine the in under-five child death in Adigrat town by using Poisson (count) regression procedure. The study uses the demographic, environmental, socioeconomic, and biological survey data to identify some of the factors that are responsible for in under-five child mortality. Before the analysis of data using the Poisson approach, the basic assumption of the Poisson model, that is, equality of the mean and variance of the number of count under-five death from individual mother was tested. The results indicated that there was no over dispersion. and under dispersion. Therefore, the final models are fit as Poisson linear model with a log link to accommodate the count nature of the response variable. The Poisson analyses show some interesting relationships between the response and predictor variation of under-five child mortality and the selected explanatory variables. In the Adigrat town the average number of under-five mortality from the individual mother in her lifetime. According to the results, Factors influencing the number of under-five deaths have been identified. The study revealed that mother's education, father's education, marital status, place of delivery, breastfeeding status, Child vaccination adaptation, sex and family income had statistically significant effect(determinants) on the number of under-five deaths in Adigrat town. However, family size, Health status of the mother, Parental care, Type of birth and Mother's age at first birth of child were found to be insignificant factors of under-five morality in these kebeles, a result which is not in line with the literature. In this study, this could be because the majority (54.1%) of mothers involved had no education. The mothers‘education is an important socio-economic predictor of under-five child mortality, that is, mortality rate decreases with increase in mothers‘education level. Many studies showed that the higher the level of maternal education, the lower the infant and child mortality. Caldwell 59 (1981) provided three explanations for the phenomenon: more educated mothers become less fatalistic about their children's illnesses, they are more capable of manipulating available health facilities and personnel and they greatly change the traditional balance of familial relationships with profound effects on childcare. In addition to these, they are more likely to have received antenatal care to give birth with some medical attendance, and to take their children at some time to see a physician. In this study, even after controlling for other variables, education of mother remained significant in the regression equations. This finding is consistent with Belaineh et al. (2007) and other studies. The study indicates that children born from working mothers have higher risk of mortality than non-working mothers. It was also found that under-five child mortality risk is lower for children of high-income parents compared to children of low-income parents. Although house holds' economic status is an important variable for reducing child mortality, in this study the variable is insignificant. This might also be due to the cross-sectional nature of the data and change in economic status of the household over time might be observed. The potential demographic, environmental, socioeconomic, and biological differences, under-five child mortality exhibits a significant variation among in Adigrat town.. Due to restriction in the software, only the educational level of mother and environmental factors were analyzed separately.

Recommendation

In this project attempt has been made to look into factor affecting the determinant under-five mortality. Now we suggest some basic recommendation that could be minimizing the problem: Promoting human's rights, empowering women and enhancing equitable access to income to enable women to make healthy decisions to safe their own lives and their child's lives as well. Effective programs to reduce early childbearing of women should be implemented so as to decrease under-five child mortality. The government/ministry of health should give greater attention to improve immunization services and concentrate on health education campaigns for mothers and for the community. There is a need for comprehensive prevention strategies that will help to further reduce child mortality. Early marriages should be discouraged and awareness about the danger of giving birth at early ages should be created through education. Health interventions should particularly be targeted towards women who are suffering from illness and weakness to allow them to continue breastfeeding

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