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Research Article

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Determinants of Under-Five Mortality in Tach- Armachiho District, North Gondar, Ethiopia

Agmas Sisay Abera[1*], Hunachew Kibret Yohannis[1]

[1]Department of Statistics, College of Natural and Computational Sciences, University of Gondar, Gondar, Ethiopia

[*]Corresponding author
Agmas SisayAbera, Department of Statistics, College of Natural and Computational Sciences, University of Gondar, Gondar, Ethiopia.

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Abstract

Background: *Under-five mortality rate, often known by its acronym U5MR, indicates the probability of dying between birth and five years of age, expressed per 1,000 live births. Globally, 16,000 children under-five still die every day. Especially in Sub-Saharan Africa every 1 child in 12, dying before his or her fifth birthday. This study aims to identify the determinants of under-five mortality among women in child bearing age group of Tach-Armachiho district using count regression models.*

Methods: *For achieving the objective, a two-stage random sampling technique (simple random sampling and systematic random sampling techniques in the first and second stages respectively) was used to select women respondents. The sample survey conducted in Tach-Armachiho district considered a total of 3815 households of women aged 15 to 49 years out of which the information was collected from 446 selected women through interviewer administrated questionnaire.*

Results: *The descriptive statistics result showed that in the district 16.6% of mothers have faced the problem of at least one under-five death. In this study, Poisson regression, negative binomial, zero-inflated Poisson and zero-inflated negative binomial regression models were applied for data analysis. Each of these count models were compared by different statistical tests. So that, zero-inflated poisson regression model was found to be the best fit for the collected data. Results of the zero-inflated Poisson regression model showed that education of husband, source of water, mother occupation, kebele of mother, prenatal care, place of delivery, place of residence, wealth of house hold, average birth interval and average breast feeding were found to be statistically significant determinants of under-five mortality.*

Conclusions: *In this study, it was found that the factors like average birth interval and average breast feeding were found to be statistically significant factors in both groups (not always zero category and always zero category) with under-five child deathwhereas education of husband, source of water, place of delivery, mother occupation and wealth index of the household have significant effect on under-five mortality under not always zero group. Place of residence, kebele of mother and prenatal care have a significant effect on under-five mortality in TachArmachiho district on inflated group.*

Keywords: Under-Five Mortality, Zero-Inflated Poisson Regression Model, Over Dispersion

Background

Mortality in childhood, particularly in the first 5 years of life, has been a major global concern in recent years. The level of under-five mortality rate is a key indicator of child well-being, including health and nutrition status. It is also a key indicator of the coverage of child survival interventions and, more broadly, of social and economic development. For infant and young children, the risk of dying is closely related to the environment in which they live. The environment depends on commitment of nation to provide proper nutrition and female education. The United Nation along with other organizations has been actively involved in reducing under-five mortality in the world. As a result, globally there have been considerable improvements in the level of under-five mortality in recent years specifically; in 2013 the death rate was 46 per 1000 live births [1]. At the country level, historical trends show that progress for most countries has been too slow and that only 12 of the 60 countries with high under-five mortality rates at least 40 deaths per 1,000 live births [1].

Neonatal mortality refers to the probability of dying within the first month of life that is death at age 0-30 days; Infant mortality is defined as the death of a live born between birth and exact age of one year. Child mortality is referred to as the probability of dying between exact ages of one and five years[2, 3]. The under-five mortality rate, often known by its acronym U5MR, indicates the probability of dying between birth and five years of age, expressed per 1000 live births [2, 4].

New estimates in Levels and Trends in Child Mortality Report 2015 released by UNICEF, the World Health Organization, the World Bank Group, and the Population Division of UNDESA, indicate that although the global progress has been substantial, 16000 children under-five still die every day. And the 53 percent drop in under-five mortality is not enough to meet the Millennium Development Goal of a two-thirds reduction between 1990 and 2015 [5].

Child's chance of survival is still vastly different based on where he or she is born. Sub-Saharan Africa has the highest under-five mortality rate in the world with 1 child in 12, dying before his or her fifth birthday which is 12 times higher than the 1 in 147 average in high-income countries [5]. All 16 countries with an under-five mortality rate above 100 deaths per 1000 live births are in Sub-Sahara Africa. As the rest of the world reduces child mortality, under-five deaths are becoming ever-more concentrated in Sub-Saharan Africa, 3.2 million deaths (nearly half the global under-five deaths) occurred in this region in 2012. Therefore, the number of under-five deaths may stagnate or even increase without more progress in the region [6]. According to the "Level and trends in child mortality Report 2013" published by the UN Inter-Agency Group for Child Mortality Estimation, Ethiopia is one of the seven high-mortality countries (together with Bangladesh, Malawi, Nepal, Liberia, Tanzania and Timor) with the greatest declines by two thirds or more in lowering child mortality between 1990 and 2012 [7]. For the five years of 2006-2010 immediately preceding the EDHS collected by department for international development survey in Ethiopia; the overall under-five mortality rate was 88 deaths per 1000 live births. Sixty-seven percent of all deaths to children under-five in Ethiopia takes place before a child's first birthday. The 2011 EDHS showed a rapid decrease in infant and under-five mortality during the five years prior to the survey compared to the period 5-9 years prior. The levels were also considerably lower than those reported in the 2005 EDHS. Infant mortality rate in Ethiopia was 59 deaths per 1000 live births, while under-five mortality rate was 88 per 1000 live births [8].

The Ethiopian Demographic and Health Survey reported 123 and 88 deaths per 1000 live births in its 2005 and 2011 reports, respectively. The recent UNICEF report puts Ethiopia's child mortality rate at 68 per 1000 live births. These figures imply that the child mortality rate in the base year 1990 was as high as 206. The reduction from 206 to 68 deaths in 1000 live births clearly shows that Ethiopia has designed sound health policies and backed them up with the necessary resources to ensure great success in implementation [9, 4]. According to UN Interagency Group for Child Mortalityreport,in 2015 the under-five mortality rate of Ethiopia was 59 per 1000 live births [10, 11].

Methods

Study Area, Study Population and Data Collection Method

Tach Armachiho is one of the districts in North Gondar Zone Amhara Regional State of Ethiopia. The district is located 814 km Northwest of Addis Ababa and 65 km North West of Gondar town with the altitude of 600-2000 meters above sea level (masl) with the temperature of 25-42°C and with annual rainfall of 800-1800 mm [12]. According to the district administrative data the district has 24 kebeles. Total population of the district is 106085 among this 54358 are males and 51727 are females with 21217 total number of households [13]. All women who are currently living at least for six months in Tach Armachiho district are the study population. The target population comprises of those women residing in Tach Armachiho district with the age of women from 15- 49 that were selected from the total population. In this study, the researcher used primary data. Primary data were conducted using interviewer administrated questionnaire and the questionnaire was collected and pre-tested by selected respondents under the supervision and monitoring of the researcher. In the preliminary, the questionnaire was prepared by English language and then it was translated to Amharic language. Enumerators engaged with the close supervision of the researcher and they trained on the methods of administering, on the contents of the questionnaires and on the objective of why the data is collected.

Sample Size Determination and Sampling Techniques

.The sample size for collecting data for this study determined by using formula of simple random sampling [14].The formula to estimate sample size is given as follows:

$$n=\frac{n_0}{1+\frac{n_0}{N}}$$

$$\text{where;} n_0=\frac{(Z_{\alpha/2})^2 s^2}{d^2}$$

n_0= initial sample size, if $\frac{n_0}{N} < 5\%$, approximately n_o= n

S = Poisson standard deviation which was calculated from pilot survey (s^2=0.209). pilot survey (of 31 observations to estimate representative maximum sample size) was preferable for this study. According to suggest that 30 representative participants from the population of interest is a reasonable minimum recommendation for a pilot study where the purpose is preliminary survey[15].

d= desired degree of precision. Most of the time 5% is desirable to increase the sample size and the precision of the study [16].

$Z_{\alpha 2}$= Z Value for the 95% level of confidence is (1.96)
N= total number of population size in the study area (in this case total number of households).
n= desired number of sample size.

Based on the above formula , the desired sample size for the study is as follows:

$$n_0=\frac{(Z_{\alpha/2})^2 s^2}{d^2}=\frac{(1.96)^2 x\, 0.209}{(0.05)^2}=\frac{0.803}{0.0025}=322$$

Since $\frac{n_0}{N}=\frac{322}{3815}=0.0844$ is very large that is greater than 5%,

$$n=\frac{n_0}{1+\frac{n_0}{N}}=\frac{322}{1+0.0844}=297$$

However, in estimating the sample size of two stage random sampling especially if the first and the second sampling techniques are different, it is often convenient to use the design effect. This has two primary uses, in sample size estimation and in appraising the efficiency of more complex plans [14]. The design effect is kept as low as possible in order for the results to be useably reliable. Unless previous surveys have been conducted or similar ones in other countries so that proxy estimates of design effectcan be utilized, a default value of 1.5 to 2.0 for design effect is typically used by the sampling practitioner in the formula for calculating the sample size. To keep the design effect as low as possible, select a systematic sample of households at the last stage, geographically dispersed, rather than a segment of geographically contiguous households [17]. By minimizing or controlling the design effect as much as possible the researcher takes 1.5 for design effect.

Finally: n_f= n*1.5=297*1.5=446

Lastly the estimated sample size has to be distributed to the four selected kebeles using proportional allocation method since all kebeles have no the same total number of households. Based on the sampling frame; Sanja kebele have 1363, Masero-demb kebele have 1231, Kokora kebele have 741 and Kembew kebele have 480 households.

Proportional allocation is given as:

$$n_i=\frac{n\,N_i}{N}$$

where, n_i= sample number of households in the i_{th} kebele.
N_i = total number of households in the i_{th} kebele.
N = total number of households in the four selected kebeles which is 3815.

Table 1: Probability Proportional to Size Allocation for the Selected Kebeles

No.	Name of kebele	Total number of households	Sample number of households
1	Sanja	1363	n_1=(446×1363)/3815=159
2	Masero-demb	1231	n_2=(446 x 1231)/3815=144
3	Kokora	741	n_3=(446×741)/3815=87
4	Kembew	480	n_4=(446×480)/3815=56
Total		3815	446

Then, to select sample households systematic sampling technique was used with the interval of

$$\frac{N_i}{n_i}=\frac{1363}{159}=8.57=\frac{1231}{144}=8.55=\frac{741}{87}=8.52=\frac{480}{56}=8.57\approx 8$$ [14].

The starting household for nieach selected kebele was selected using table of random number methods from the list.

To select samples, two stage random sampling followed by simple and systematic random sampling techniques was applied. Under this sampling technique, there are two stages to be followed. At first stage, by using the frame of the kebeles samples of kebeles were selected (primary sampling units) using simple random sampling technique through table of random number method. By considering the homogeneity of the risk of under-five mortality within the district, among 24 kebeles four kebeles were selected. Accordingly, Sanja, Kembew, Maserodemb and Kokora kebeles were selected. At second stage, households (Secondary sampling unit) using systematic random sampling technique were selected. Finally, one woman was randomly selected and the study conducted on the selected women by using interviewer administrated questionnaire method.

Study Variables

The response variable for this study was the number of under-five death experienced by individual mother. Children who were born alive and later die before reaching their fifth birthday was considered.

Methods of Data Analysis

Poisson and Negative Binomial Regression Model

The Poisson regression model is often considered as a benchmark model for modelingcounts data. This model dominates the count data modeling activities as it suits the statistical properties of count data and is flexible to be reparameterised into other form of distributional functions [18, 19]. Though practically it is inadequate for its restrictive assumptions, still the Poisson regression model is the simplest model and lends a good starting point to model count data. In this model, the response variable is assumed to be independent and follows a Poisson distribution.

Poisson regression assumes a Poisson distribution, characterized by a substantial positive skewness with variance equals mean. It tends to fit such data better than the linear regression model. However, if the variance is larger than the mean, it induces deflated standard errors and inflated standardized normal (i.e. Z-normal) values, resulting in increased Type I errors that make Poisson regression less adequate. Some researchers suggest that, when there is an overdispersion which does not arise from an excess of zeros, it is better to use other models, such as negative binomial which can take care of the over dispersion problem [20,21].

Poisson regression model is used when the dispersion parameter becomes zero ($\alpha=0$) otherwise negative binomial regression model is better. The negative binomial distribution is one of the most widely used distributions when modeling count data that exhibit variation that Poisson distribution cannot explain. When the Poisson model assumption fails, this model may fit better, and addresses the issue of overdispersion by introducing a dispersion parameter to accommodate for unobserved heterogeneity in count data. However, this is true only if it is not attributed to excess zeros [22, 23].The negative binomial regression model may not be well flexible to handle excess zeros. This motivates the development of zero-inflated count model to model excess zeros in addition to overdispersion. This technique was first introduced by [24]. In such cases, one can use the zero- inflated Poisson or zero- inflated negative binomial model to fit the data.

Zero-Inflated Poisson and Zero-Inflated Negative Binomial Regression Model

Zero-inflated Poisson (ZIP) model has been first considered by as a mixture of a zero-point mass and a Poisson[24]. This model assumes two latent groups, one is capable of having positive counts and the other will always have zero count [25]. Similarly considers the negative binomial model case. When there are excess zeros and high variability in the non-zero outcomes, ZIP models are less adequate than ZINB models.

The probability mass function for zero-inflated Poisson regression model is given as:

$$P(Y_i=y_i)=\begin{cases}\phi_i+(1-\phi_i)\,P(Y=0) & \text{if } y_i=0\\ (1-\phi_i)\,P(Y=y_i) & \text{if } y_i=1,2,\ldots\end{cases}$$

If Yi are independent random variables 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 $\phi_i$and produces only zeros, while the other state occurs with probability $(1-\phi_i)$ and leads to a standard Poisson count with mean λ_i. In general, the zeros from the first state are called structural zeros and those from the Poisson distribution are called sampling zeros. This two-state process gives a simple two-component mixture distribution with probability mass function:

$$P(Y_i=y_i)=\begin{cases}\phi_i+(1-\phi_i)e^{-\lambda_i} & \text{if } y_i=0\\ (1-\phi_i)\dfrac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} & \text{if } y_i=1,2,\ldots\end{cases}$$

This is denoted by $Y_i \sim ZIP(\lambda_i, \phi_i)$ such that $0\leq\phi_i<1$, where λiis the mean of the non-zero outcomes that can be modeled with the associated explanatory covariates using a natural logarithmic link function as:

$$\ln(\lambda_i)=\ln(N_i)+Xi'\beta$$

where $X_i=(1,x_i1, x_i2, \ldots, x_{ik})'$ is a (k+1)x1 vector of explanatory variable of the i[th] subject and β is (k+1)x1 vector of regression coefficient parameters. $\phi_i(0<\phi i<1)$ is the probability of an excess zero (being in the zero mortality state) determined by a logit model [24, 26].To predict membership in the "Always Zero" group, use the same variables or use a smaller subset of the variables or even different variables altogether and extended it by specifying a logit model form in order to capture the influence of covariates on the probability of extra zeros: that is:

$$\ln\left(\frac{\phi_i}{1-\phi_i}\right)=Z'_i\gamma$$

Equivalently

$$\phi_i=\frac{\exp(Z'_i\gamma)}{1+\exp(Z'_i\gamma)} \qquad i=1,2,\ldots, n$$

Where $z_i=(1,z_i1,z_i2,\ldots,z_{iq})'$ is a (q+1)x1 vector of explanatory variable for the zero-inflation part model of the i[th] mother and $\gamma=(\gamma_0, \gamma_1,\ldots,\gamma_q)'$ is (q+1)x1 vector of zero-inflated regression coefficient parameters to be estimated. Unlike the Poisson distribution which is determined by a single parameter, the ZIP distribution is determined by two parameters, λ_i and ϕ_i. The covariates that formulate the mean of accident frequency (λ_i) in a Poisson regression model could be the same as or different from those of explaining the probability of extra zeros (ϕ_i) in a logistic model.

Thus, the above model incorporates extra zeros than the original Poisson model in which i. The ZIP model is a special case of a two-class finite mixture models with mean and variance, respectively:

$E(Y_i)=\lambda_i(1-\phi_i)$ and $Var(Y_i)=\lambda_i(1-\phi_i)(1+\phi_i\lambda_i)$

Note that when ϕ_i is equal to zero, then the mean of a ZIP model is the same as that of a Poisson model, and the ZIP model is essentially the same as a Poisson model. It can be further verified by the variance to mean ratio that a ZIP model is suitable to capture over-dispersed data in view of the fact that its variance is generally greater than its mean value. The ratio $\phi/1-\phi$ plays a similar role as the dispersion factor α in a NB model and it is employed to capture the overdispersion characteristics of the analyzed data.

$$\frac{V(y)}{E(y)}=1+(1-\phi)\lambda=1+\left(\frac{\phi}{1-\phi}\right)E(y)$$

An alternative formulation for the ZIP which is found to be more useful for interpretation is:

$$P(Y_i=y_i)=\begin{cases}1-P & \text{if } y_i=0\\ P\frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i![1-e^{-\lambda_i}]} & \text{if } y_i=1,2,\ldots\end{cases}$$

where $p=(1-\phi_i)(1-e^{-\lambda_i})$ is the probability of observing at least one child death count. For observations $y_1, y_2,\ldots,y_n$ the likelihood function for ZIP model is given by [27].

$$L=\prod_{y_i=0}\left\{\phi_i+(1-\phi_i)e^{-\lambda_i}\right\}\prod_{y_i\neq 0}\left\{(1-\phi_i)\frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}\right\}$$

Taking log on both sides the log- likelihood function is given by:

$$\ln(L)=\sum_{i=1}^{n}\left\{\begin{matrix}I(y_i)\ln\left(\phi_i+(1-\phi_i)e^{-\lambda_i}\right)+\left(1-I(y_i)\right)(\ln(1-\phi_i)\\ +y_i\ln\lambda_i-\lambda_i-\ln\Gamma(y_i+1))\end{matrix}\right\}$$

where $I(\cdot)$ is an indicator function that is one if the response (yi) equals zero, and zero otherwise.

The first and second derivatives of ln (L) with respect to β and γ are:

$$\frac{\partial\ln(L)}{\partial\beta_j}=\frac{\partial\ln(L)}{\partial\lambda_i}\frac{\partial\lambda_i}{\partial\beta_j}=\sum_{i=1}^{n}\left\{I_{(y_i=0)}\left[\frac{-(1-\phi_i)\lambda_i e^{-\lambda_i}}{\phi_i+(1-\phi_i)e^{-\lambda_i}}\right]+I_{(y_i>0)}\left[y_i-\lambda_i\right]\right\}x_{ij},\quad j=1,2,\ldots,p$$

$$\frac{\partial\ln(L)}{\partial\gamma_r}=\frac{\partial\ln(L)}{\partial\phi_i}\frac{\partial\phi_i}{\partial\gamma_r}=\sum_{i=1}^{n}\left\{I_{(y_i=0)}\left[\frac{1-e^{-\lambda_i}}{\phi_i+(1-\phi_i)e^{-\lambda_i}}\right]-I_{(y_i>0)}\left[\frac{1}{1-\phi_i}\right]\right\}z_{ir},\ r=1,2,\ldots,q$$

where p and q are the number of covariates for non-zero group and for zero group respectively. To apply the zero-inflated Poisson model in practical modeling situations, the parameters λ_i and ϕ_i can be obtained through the following link functions [24]:

$$\ln(\lambda)=X\beta \quad \text{and} \quad \ln\left(\frac{\phi}{1-\phi}\right)=Z\gamma$$

Where $X_{(n\times(k+1))}$ and $Z_{(n\times(q+1))}$ are covariate matrixes, and β and γ are, respectively, unknown parameter vectors with (k+1)x1 and (q+1)x1 dimension [27]. Maximum likelihood estimates for β and γ can be obtained using standard approaches for mixture model.

The use of the logit link function for ϕ constrains ϕ_i to lie between 0 and 1 and will problematic when $\phi = 0$, a case of interest as this corresponds to the standard Poisson regression model.

Model Comparisons for Under-Five Mortality

The response variable in this study was the number of under-five deaths per mother in her life time. Such type of data is well fitted using count data regression models rather than other regression models. In this study different possible count data models were considered. To identify the most appropriate and well fitted count regression model for the collected data, loglikelihood ratio test, Akaike information criteria and Bayesian information criteria were used.

Results

Descriptive Statistics

The data was analyzed from women of child bearing age in the study area. Out of the total number of women considered in the sample 83.4% of the mothers have not faced any U5D in their lifetime. From the sampled women, the proportion of experiencing under-five mortality was about 16.6 percent.

Table 2:Number of Mothers That Experienced Under-Five Deaths

Number of under-five deaths per mother	Number of mothers		Percentage	Cumulative Percentage
	Urban	Rural		
0	183	189	83.4	83.4
1	19	32	11.4	94.8
2	7	11	4.0	98.9
3	2	2	0.9	99.8
4	1	0	0.2	100
Mean = 0.23	Variance = 0.34		Median = Mode = 0	

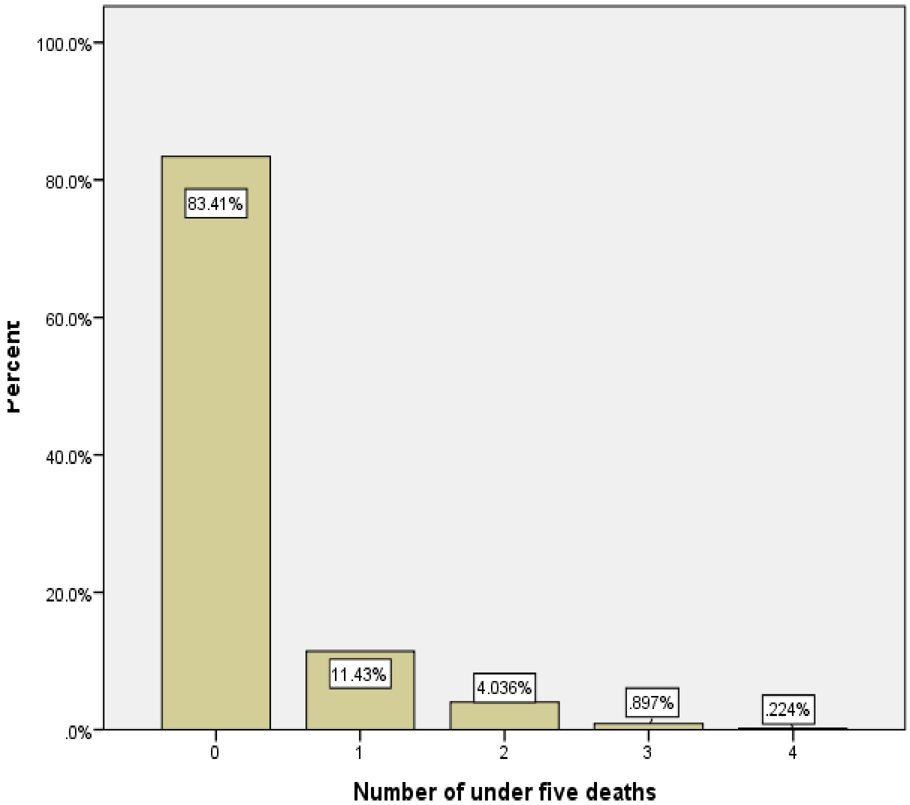

Figure 1:A Bar Chart of the Number of U5D Per Mother

Table 2 and Figure 1 above showed the number and percentage of U5D that the mothers in the sample have encountered in their lifetime. Large numbers of under-five mortality per mother were less frequently observed, which seems highly skewed to the right with excess zeroes. This perhaps an indication that count data models with excess zeroes may be take into account.

Table 3: Summary Statistics of Some Important Variables Related to Under-Five Mortality

Variables with category		Number of under-five death per mother						
		0	**1**	**2**	**3**	**4**	**Mean**	**St.Deviation**
Education of the mother	No education	266	37	13	4	1	0.25	0.616
	Primary	59	10	5	0	0	0.27	0.580
	Secondary and above	47	4	0	0	0	0.08	0.272
Place of residence	Rural	189	32	11	2	0	0.26	0.581
	Urban	183	19	7	2	1	0.20	0.585
Age at first birth	<20	243	40	14	4	1	0.28	0.643
	>=20	129	11	4	0	0	0.13	0.414
Education of husband	No education	255	42	15	4	0	0.27	0.606
	Primary	73	4	3	0	1	0.17	0.608
	Secondary and above	44	5	0	0	0	0.10	0.306
Source of water	Have piped/ tube water	328	41	15	2	1	0.21	0.553
	Otherwise	44	10	3	2	0	0.37	0.740
Availability of toilet facility	Have toilet facility	144	17	5	1	1	0.20	0.575
	Otherwise	228	34	13	3	0	0.25	0.588
Place of delivery	Home	262	39	17	3	1	0.27	0.629
	Health center	110	12	1	1	0	0.14	0.429

Child vaccination adaptation	Mother adapted	316	26	7	2	0	0.13	0.434
	vaccinating children							
	Otherwise	56	25	11	2	1	0.60	0.856
Distance of health center	Distance < 8 km	319	45	15	2	1	0.22	0.561
	Distance >=8 km	53	6	3	2	0	0.28	0.701
Kebele of mother	Sanja	128	23	7	1	0	0.25	0.562
	Masero-demb	126	13	4	0	1	0.17	0.533
	Kokora	69	11	5	2	0	0.31	0.687
	Kembew	49	4	2	1	0	0.20	0.585
Occupation of mother	House wife	274	40	14	4	1	0.17	0.461
	Others	98	11	4	0	0	0.25	0.618
Occupation of husband	Farmer	271	44	16	4	1	0.27	0.634
	Merchant	15	2	0	0	0	0.12	0.332
	Others	86	5	2	0	0	0.10	0.363
Wealth index	Poor	135	20	13	2	0	0.31	0.662
	Medium	127	23	2	2	0	0.21	0.523
	Rich	110	8	3	0	1	0.15	0.525
Health status of mother	Have disease	11	2	1	0	0	0.29	0.611
	Otherwise	361	49	17	4	1	0.23	0.583
Prenatal care	Give prenatal care	211	20	7	1	0	0.15	0.464
	Otherwise	161	31	11	3	1	0.32	0.686
Average birth interval	Interval <2 years	92	23	6	2	1	0.36	0.725
	Interval >=2 years	280	28	12	2	0	0.18	0.510
Average breast feeding	Feeding < 2 years	156	34	12	3	1	0.34	0.700
	Feeding >= 2 years	216	17	6	1	0	0.13	0.437
Total		372	51	18	4	1	8.86	21.463

Table 3 presents summary statistics of the explanatory variables that directly influence the risk of under-five mortality. The variables which are included in the study are education of mother, place of residence, age at first birth, education of husband, source of water, availability of toilet facility, place of delivery, child vaccination adaptation, distance of health center, kebele of mother, occupation of mother, occupation of husband, wealth index, health status of mother, prenatal care, average birth interval and average breast feeding.

The total number of women considered in this study was 446 of which 74 of them experienced under-five mortality. Generally, on average 0.26 of under-five deaths occurred in rural areas with the standard deviation of 0.581, while 0.20 average numbers of deaths happened in urban areas and had the same standard deviation with rural residential. Of the total number of under-five deaths per woman, a smaller number of under-five deaths in urban areas had been occurred when it was compared with rural under-five deaths. The mean number of under-five deaths per mother was 0.25, 0.27 and 0.08 for no education, primary and secondary and above educational level of mother respectively. In this case the maximum standard deviation is occurred from no education which was 0.616. In the same way, the average numbers of under-five deaths for husband were 0.27, 0.17 and 0.10 for no education, primary and secondary and above educational level respectively.

Another maternal variable that possibly has a strong bearing on the survival prospects of a child is the mother's age at the time of first birth. Regarding mother's age at first birth, the mean number of under-five mortality was 0.28 for mothers who started their first birth below the age of 20 and the death showed a high variability with a standard deviation of 0.643. However, on the average 0.13 number of under-five deaths existed for the mothers who delivered their first children on the age of 20 and above. It also showed less variation of child deaths than for the mothers who delivered their first child before the age of 20. Besides mothers who delivered their children at home faced more under-five mortality than mothers who delivered their children at health center. The mean numbers of under-five mortality for mothers who delivered their children at home and at health center were 0.27 and 0.14 respectively.

Concerning kebeles, Kokora and Sanja had the highest mean number of under-five deaths per mother were 0.31 and 0.25 respectively, while Kembew and Masero-demb kebeles had the third and fourth smallest mean number of under-five deaths per mother which were 0.20 and 0.17 respectively. As far as the distance of health facilities was concerned, mean number of under-five death per mother increased with an increase in the distance of health facilities from mothers' home. Specifically, the mean under-five death was 0.22 for women's home distance from health center was below 8 kilometer, 0.28 mean number of under-five death was occurred for those mothers whose home distance from health center was eight and above kilometer. Whereas, the variation of under-five mortality was higher for the mother's home had long distance from health centers than the homes which had smallest distance.

When child vaccination adaptation of mother was assessed, the mean number of under-five mortality per mother was 0.60 for mothers who did not adapted vaccinating their children with higher standard deviation of 0.856. As expected, less mean number of under-five deaths (0.13) was encountered in women who adapted vaccinating their children with a standard deviation of 0.434. Similarly, 0.25 mean number of under-five death occurred in households without toilet facility and 0.2 mean number of under-five mortality was happened in toilet facility user households.

Regarding wealth index 0.31, 0.21 and 0.15 mean number of under-five death were occurred for poor, medium and rich households respectively. Even though mothers gave prenatal care to their children, on the average 0.15 under-five deaths per mother occurred in mothers of giving prenatal care for their children. However, mothers who did not give prenatal care acquired 0.32 average under-five deaths.

Model Comparisons for Under-Five Mortality

The starting point of count regression models are fitting Poisson regression model. The fitted Poisson regression model is then tested for overdispersion. If so, the negative binomial model is an immediate solution to accommodate this overdispersion. However, the overdispersion might be occurred due to excess zeroes. This brings the zero-inflated models into the picture. Thus, in order to select an appropriate model which fits the data well, the standard Poisson, negative binomial, zero-inflated Poisson and zero-inflated negative binomial regression models were considered.

Goodness of Fit of the Model and Test of Overdispersion

In the beginning the overall goodness of fit of the model using the Pearson chi-square and deviance-based chi-square (likelihood ratio) test statistic were checked. Therefore, the Pearson chi-square value was 491.996 with p=0.0104 and the deviance chi-square test value at 23 degree of freedom was 101.77 with p= 0.0001** which implies that Poisson regression model was a good fit of the observed data. Then, the equi-dispersion assumption of the model was performed.

Table 4: Test for Goodness of Fit and Overdispersion Between PRM and NBRM

Test	Estimate	Poisson	Negative binomial
Pearson chi-square	Value	491.996	398.440
	Degree of freedom	422	422
	Value/df	1.166	0.944
Alpha			0.742
Likelihood-ratio test of alpha $X^2(1)$= 6.97			P = 0.004**

Overdispersion can be assessed using dispersion index through dividing variance of the response by its mean. Accordingly, the index value 1.478 is greater than one; it is an indicator of existence of overdispersion, that is, the true variance is greater than the true mean which is an indication of assumption of Poisson regression model is violated. Pearson chi-square value over the degree of freedom is greater than one in Poisson regression model. This is a possible sign of overdispersion. Moreover, it is desirable to apply a formal statistical test of dispersion. The value of the likelihood-ratio test of dispersion parameter alpha was x+= 6.97 with p-value = 0.004**. Therefore, the chi-square test at one degree of freedom (6.97 with p-value of 0.004) found to be statistically significant and it indicates that there is an overdispersion. As a result, the negative binomial regression model was appropriate for the analysis of under-five child mortality data as compared to the Poisson model.

The negative binomial regression model had smaller AIC (479.769) and BIC (541.793) values than the standard Poisson regression model to fit the U5M data. Further, the likelihood ratio test was used to compare the fit of negative binomial regression model with Poisson regression model. Based on that, likelihood ratio test of negative binomial regression model is found to be statistically significant which is ($X^2(1)$ = 8.322, p-value=0.002**). These results showed that negative binomial regression model was a better fit than Poisson regression model.

So far existence of overdispersion was assessed; now it is the time to check the cause of overdispersion. It might have happened due to heterogeneity of data or excess of zeros. In cases of overdispersion, the zero-inflated Poisson model typically fits better than a standard Poisson model. When the major source of over dispersion is a preponderance of zero counts, the resulting overdispersion cannot be modeled accurately with the negative binomial regression model. An alternative way for modelingthis type of data is the zero-inflated Poisson or zero-inflated negative binomial regression model which takes into account the excess of zeroes.

Now zero inflated regression models can be fitted to analyze the risk factors in under-five child mortality. After fitting zero inflated models, then test H_0: $\phi = 0$ versus Ha: $\phi > 0$ to identify whether the overdispersion is due to the presence of excess zeros or high variability in the nonzero outcomes. If the null hypothesis for testing of the inflation parameter H_0: $\phi = 0$ is not rejected, then ZINB model is not appropriate and the overdispersion problem is due to the presence of excess zero outcomes. However, if both parameters α in NBRM and ϕ in ZINB are significantly different from zero, then the zero-inflated negative binomial regression model is more appropriate to fit the data.

Model Selection

In order to select the best fit count regression model, different statistical tests were used. Among this likelihood ratio test, Vuong test, mean absolute difference, Pearson sum of predicted and actual probability and residual plots for estimated models were considered.

Table 5: Comparison of Mean Observed and Predicted Count

Model	Maximum Difference	At Value	Mean |Diff|	Likelihood	BIC	AIC
PRM	-0.034	1	0.007	-233.045	547.893	486.091
NBRM	0.013	2	0.003	-228.885	541.793	479.769
ZIP	0.005	1	0.001	-209.893	524.873	459.786
ZINB	-0.004	0	0.004	-209.893	527.094	461.786

Table 6: Predicted and Actual Probabilities for PRM, NBRM, ZIP and ZINB Models

PRM					NBRM				
Count	Actual	Predicted	|Diff|	Pearson	Count	Actual	Predicted	|Diff|	Pearson
0	0.834	0.815	0.019	0.195	0	0.834	0.835	0.000	0.000
1	0.114	0.149	0.035	3.590	1	0.114	0.122	0.007	0.188
2	0.040	0.028	0.013	2.526	2	0.040	0.028	0.013	2.579
3	0.009	0.006	0.003	0.564	3	0.009	0.009	0.000	0.001
4	0.002	0.001	0.001	0.206	4	0.002	0.004	0.001	0.252
5	0.000	0.000	0.000	0.142	5	0.000	0.002	0.002	0.751
6	0.000	0.000	0.000	0.030	6	0.000	0.001	0.001	0.369
7	0.000	0.000	0.000	0.006	7	0.000	0.000	0.000	0.190
8	0.000	0.000	0.000	0.001	8	0.000	0.000	0.000	0.101
9	0.000	0.000	0.000	0.000	9	0.000	0.000	0.000	0.055
Sum	1.000	1.000	0.070	7.259	Sum	1.000	1.000	0.025	4.486
ZIP					ZINB				
Count	Actual	Predicted	|Diff|	Pearson	Count	Actual	Predicted	|Diff|	Pearson
0	0.834	0.838	0.004	0.010	0	0.834	0.838	0.004	0.010
1	0.114	0.110	0.005	0.090					
2	0.040	0.038	0.003	0.083					
3	0.009	0.011	0.002	0.116					
4	0.002	0.003	0.000	0.040					
5	0.000	0.001	0.001	0.297					
6	0.000	0.000	0.000	0.069					
7	0.000	0.000	0.000	0.015					
8	0.000	0.000	0.000	0.003					
9	0.000	0.000	0.000	0.001					
Sum	1.000	1.000	0.015	0.724	Sum	1.000	0.838	0.004	0.010

The BIC's and AIC's in the above Table 5 indicates a strong preference of the ZIP over the Poisson model and the ZINB over the negative binomial model. Similarly, when mean absolute difference, BIC and AIC values were assessed ZIP model had the minimum values from the other three models. In addition to this in Table 6among the four models, the one which has the smallest Pearson sum of the predicted and actual probability is the best model. From the table, ZIP has the minimum Pearson sum of the predicted and actual probabilities than other count models. However, ZINB seems to have the smallest Pearson sum, but it has the Pearson sum of predicted and actual probability for zero count only this might be no improvement in ZINB model other than ZIP model.

The most common assessment of overall model fit in ZIP regression model is the deviance test statistic which compares the null model and the model containing the factors. The value of deviance test statistic gives us a chi-square value of 72.13 with p-value of 0.001**. Since deviance test was found to be significant; So that, adding the predictors to the model has not significantly increased the ability of prediction of ZIP model on under-five mortality.

Table 7: Tests and Fit Statistics for Model Comparisons

PRM	**BIC=547.893**	**AIC= 486. 091**	**Prefer**	**Over**	**Evidence**
Vs NBRM	BIC=541.793	dif=6.100	NBRM	PRM	Positive
	AIC=479.769	dif=6.322	NBRM	PRM	
	LRX2=8.322	prob=0.002	NBRM	PRM	P= 0.002
	BIC=524.873	dif=23.02	ZIP	PRM	Very strong
Vs ZIP	AIC=459.786	dif=26.305	ZIP	PRM	
	Vuong= 3.124	prob=0.001	ZIP	PRM	P= 0.001
	BIC=527.094	dif=20.799	ZINB	PRM	Very strong
Vs ZINB	AIC=461.786	dif=24.305	ZINB	PRM	
NBRM	**BIC=541.793**	**AIC=479.769**	**Prefer**	**Over**	**Evidence**
Vs ZIP	BIC=524.873	dif= 16.920	ZIP	NBRM	Very strong
	AIC=459.786	dif= 19.983	ZIP	NBRM	
Vs ZINB	BIC=527.094	dif= 14.699	ZINB	NBRM	Very strong
	AIC=461.786	dif= 17.983	ZINB	NBRM	
ZIP	**BIC=524.873**	**AIC= 459.786**	**Prefer**	**Over**	**Evidence**
Vs ZINB	BIC=527.094	dif= -2.221	ZIP	ZINB	Strong
	AIC=461.786	dif= -2.000	ZIP	ZINB	
	LRX2=0.000	prob= 0.500	ZIP	ZINB	p=0.500

When the log-likelihoods of ZIP and ZINB models were observed in Table 7 there was virtually no difference in their log-likelihoods indicated that the ZINB model did not improve the fit over the ZIP model. Moreover, the likelihood ratio test was used to compare the fit of the ZIP with ZINB regression models. Table 7 showed that the likelihood ratio test at one degree of freedom is found to be non-significant (X^2=0.000 and p-value= 0.500), which indicates that ZIP regression model more explains the observed data than ZINB regression model. These are not the only evidences of the preference of ZIP model over ZINB model but also, the chi-square test statistic of dispersion parameter ln (alpha), which is calculated from fitting the ZINB model, is found to be non-significant (Z= 0.63 ; p-value=0.529). This result showed that ZIP model describes the number of under-five deaths very well than ZINB model.

Comparison of ZIP model with the standard Poisson regression model using Vuong test statistic, by testing the null hypothesis showed that both models are equally/similar to the observed distribution. The resulting Vuong test statistic between ZIP and standard Poisson was found to be statistically significant (z=6.01; p-value = 0.000**), demonstrating that standard Poisson regression model less reflects the observed data than ZIP regression model. This is because of the presence of excess zeros in the observed data. Moreover, Vuong test is used to compare NB versus ZINB regression models. Based on that, the test statistic was (z=14.44 with p-value = 0.000**). Hence, ZINB regression model more accurately fits the number of under-five deaths as compared with the standard negative binomial regression model.

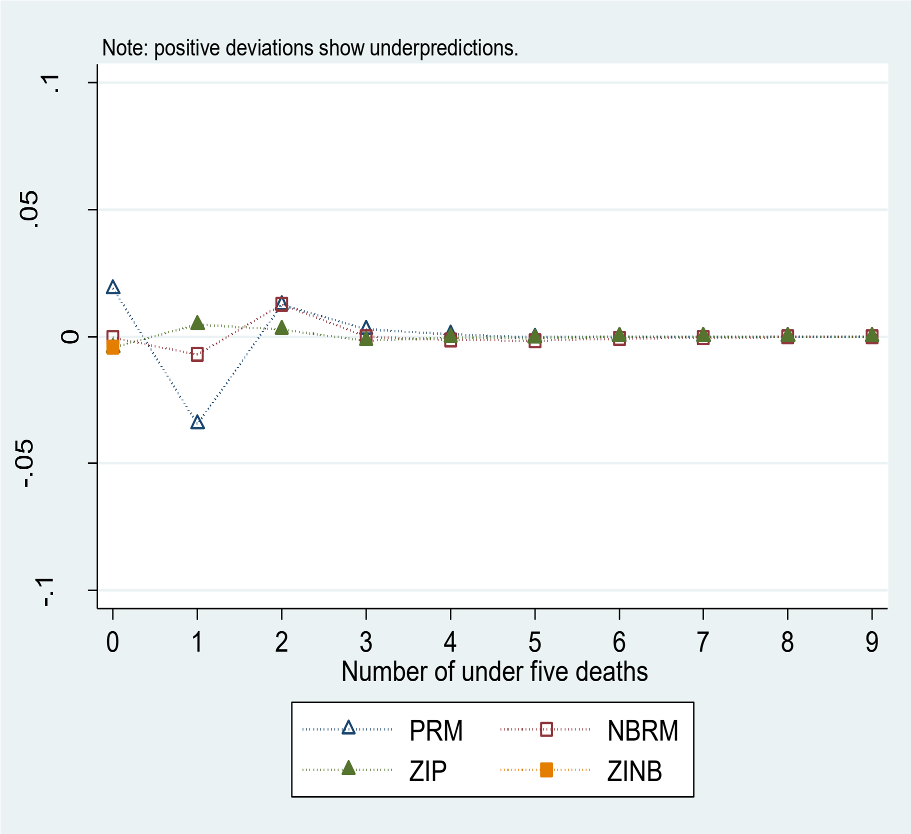

Figure 2: Observed Minus Predicted Probabilities for the Four Models

Before interpreting the results, let's figure out which model fits best for under-five child deaths. Figure 2 plots the observed proportion minus the predicted probability at each count for each of the four models. From graph, values above zero on the y-axis denote more observed counts than predicted, while those below zero indicate less observed counts than predicted. It is clear that the Poisson model provides the worst fit. At 0 under-five mortality the observed proportion predicts above zero and it is higher than the expected; at 1 under-five mortality, the reverse occurs. This is not surprising since the Poisson model is unable to account for the large proportion of zeros. While the negative binomial is a substantial improvement over the Poisson, at 1 under-five mortality there is some underestimation of the proportion. The ZIP and ZINB models were virtually indistinguishable on the plot and both fit the data quite well. Based on the formal tests and the figure, the ZIP model would appear to be the best fit.

Lastly, ZIP regression model is found to be the most appropriate model for our under-five mortality data. This fits the data better than the other possible candidate count regression models.
Next in the discussion part, the results of ZIP regression model were discussed.

Discussion and Interpretation of the Results

Results in Table 8and 9provide estimates of the effect of some selected variables on the mortality of children. A distinction has to be made between the parameters in the non-zero model predicting the mean response and the parameters for estimating the probability of zero-inflation model. The interpretation of the coefficients in the non-zero group was the same as that of standard Poisson regression model. The factors such as education of husband, source of water, place of delivery, mother occupation, wealth index, average birth interval and average breast-feeding time were found to have statistically significant effect with predictors of this count outcome. But the rest of the predictors were found to be statistically not-significant with underfive child death.

Table 8:Parameter Estimation of the Final (ZIP) Model for Not Always Zero Group

Predictors	β	SE	Z	Sig.	IRR	95% C.I for IRR	
						Lower	Upper
EDUMOTHER (No education)							
Primary	0.097	0.299	0.32	0.746	1.096	0.603	1.994
Secondary and above	0 .156	0.637	0.24	0.807	0.954	0.282	3.227
RESIDENCE (Rural)							
Urban	-0.167	0.308	-0.54	0.588	0.846	0.463	1.548
AGEAFIRBIRTH (Age <20)							
Age >= 20	0 .302	0.290	1.04	0.298	1.352	0.765	2.390
EDUHUSBAND(No education)							
Primary	0.520	0.345	1.51	0.132	1.681	0.856	3.303
Secondary and above	-1.268	0.527	-2.41	0.016*	0.282	0.100	0.791
SOWATER (Otherwise)							
Have tube water	-1.097	0.364	-3.01	0.003**	0.334	0.164	0.681
TOILETFACILITY(Otherwise)							
Have toilet facility	-0.170	0.228	-0.74	0.457	0.844	0.539	1.320
PLACEOFDELIVERY(Home)							
Health center	-1.403	0.348	-4.03	0.000**	0.246	0.124	0.487
CHILDVACCIN(Otherwise)							
Mother adapted							
vaccinating children	-0.142	0.267	-0.53	0.595	0.868	0.514	1.464
DISTANCO(Dist.<8km)							
Distance >= 8 km HEAL	0.358	0.482	0.74	0.458	1.431	0.556	3.684
KEBELEOFMOTHER(Sanja)							
Masero-demb	-0.318	0.378	-0.84	0.400	0.728	0.347	1.526
Kokora	0.420	0.435	0.97	0.334	1.523	0.649	3.575
Kembew	-0.130	0.638	-0.20	0.838	0.878	0.251	3.068
MOTHEROCCUP(House wife)							
Others	0.637	0.270	2.36	0.018*	1.891	1.114	3.208
HUSBANDOCCUP(Farmer)							
Merchant	-0.477	0.768	-0.62	0.535	0.621	0.138	2.798
Others	-0.386	0.419	-0.92	0.357	0.680	0.299	1.546
WEALTH (Poor)							
Medium	-0.220	0.257	-0.86	0.391	0.803	0.485	1.327
Rich	-0.752	0.335	-2.25	0.025*	0.471	0.244	0.909
HEALTHSTATUS(Otherwise)							
Have disease	-1.097	0.564	-1.94	0.052	0.334	0.110	1.009
PRENATALCARE(Otherwise)							
Give prenatal care	-0.428	0.260	-1.65	0.100	0.652	0.392	1.085
AVEBIRINTE(Interval <2 year)							
Interval >= 2 years	-1.533	0.354	-4.33	0.000**	0.216	0.108	0.432

AVEBREFEE(Feeding<2 years)							
Feeding >=2 years	-1.352	0.347	-3.89	0.000**	0.259	0.131	0.511
Constant	-1.694	0.567	-2.99	0.003**	0.184	0.060	0.558
LnTOTAL-NUMBCHILD	1 (offset)						

Note: - The categories in parenthesis are the reference groups; β – Regression coefficient; SE – Standard Error; Sig. – Significance; IRR-Incidence Rate Ratio; * - significant at 95% confidence level; ** - significant at 99% confidence level.

Table 9: Parameter estimation of the final (ZIP) model for the inflated (always zero) group.

Predictors	β	SE	Z	Sig.	Exp(β)	95% C.I for Exp(β)	
						Lower	Upper
EDUMOTHER(No education)							
Primary	0.424	0.292	1.45	0.146	1.529	0.863	2.708
Secondary and above	-0.398	0.563	-0.71	0.480	0.673	0.223	2.025
RESIDENCE (Rural)							
Urban	-2.442	0.959	-2.55	0.010*	0.087	0.013	0.570
AGEAFIRBIRTH (Age <20)							
Age >= 20	-0.357	0.279	-1.28	0.201	0.700	0.405	1.210
EDUHUSBAND (No education)							
Primary	-0.332	0.308	-1.08	0.281	0.717	0.392	1.312
Secondary and above	-0.318	0.490	-0.65	0.516	0.727	0.278	1.902
SOWATER (Otherwise)							
Have tube water	-0.549	0.327	-1.68	0.093	0.578	0.305	1.096
TOILETFACILITY (Otherwise)							
Have toilet facility	-0.055	0.223	-0.25	0.805	0.946	0.611	1.466
PLACEOFDELIVERY(Home)							
Health center	0.121	0.310	0.39	0.695	1.130	0.615	2.071
CHILDVACCIN(Otherwise)							
Mother adapted							
vaccinating children	-1.162	0.740	1.57	0.116	0.313	0.073	1.333
DISTANCOHEAL(Dist.<8km)							
Distance >= 8 km	0.181	0.418	0.43	0.664	1.199	0.528	2.720
KEBELEOFMOTHER(Sanja)							
Masero-demb	2.592	1.133	2.28	0.022*	13.36	1.451	23.002
Kokora	1.696	0.718	2.36	0.018*	5.452	1.334	22.278
Kembew	1.205	0.495	2.43	0.015*	3.336	1.264	8.802
MOTHEROCCUP(House wife)							
Others	0.130	0.271	0.48	0.631	1.139	0.670	1.937
HUSBANDOCCUP(Farmer)							
Merchant	-0.853	0.741	-1.15	0.250	0.426	0.100	1.821
Others	-0.181	0.392	-0.46	0.644	0.835	0.387	1.799
WEALTH (Poor)							

Medium	-0.120	0.236	-0.51	0.609	0.886	0.559	1.407
Rich	0.119	0.309	0.38	0.704	1.126	0.614	2.065
HEALTHSTATUS (Otherwise)							
Have disease	0.107	0.538	0.20	0.842	1.113	0.388	3.192
PRENATALCARE(Otherwise)							
Give prenatal care	-1.816	0.735	-2.47	0.014*	0.163	0.038	0.687
AVEBIRINTE(Interval <2 year)							
Interval >= 2 years	-1.891	0.800	-2.36	0.018*	0.151	0.031	0.724
AVEBREFEE(Feeding<2 years)							
Feeding >=2 years	-2.555	0.968	-2.64	0.008**	0.078	0.012	0.518
Constant	1.121	0.492	2.28	0.023*	3.069	1.169	8.053

Note: - The categories in parenthesis are the reference groups; β – Regression coefficient; SE – Standard Error; Sig. – Significance; Exp (β)- Odds ratio; * - significant at 95% confidence level;
** - significant at 99% confidence level.

The findings of the study showed that education of husband was found to be a significant factor on under-five child mortality. Those children that were born from a father who have secondary and above education level, 71.8% less likely to risk of under-five deaths as compared to being born to non-educated father by keeping the other predictors constant. Similar results were obtained by [28, 29]. This may be due to the fact that educated husbands give better care for their children, fulfill quality food, supporting their wives before and after delivery time and immunizing their children at the right time.

Source of drinking water was also found to have a significant effect on under-five mortality. The findings of this study showed that mothers who used water from unprotected sources were at a higher risk of experiencing under-five death than those who used pipe/tube water. The risk of under-five mortality for those children whose mothers used unprotected source of water was 66.6% higher than those who used piped/tube water supply. Similar findings were obtained by [30, 31].

Place of delivery was also investigated as a significant effect factor for under-five child deaths, such that children born in health centers had decreased the risk to death compared to those children born at home. That are children who were born at health center were less likely to die before age five than those who were born at home. The risk of under-five deaths of those mothers who delivered at health center showed that a 75.4% decrement than mothers who delivered their children at home. This was similar with the study of [32, 30].

Mother's occupation was also found to have a significant effect with under-five mortality, such that children born from mothers who have other type of work were 89% times more likely to die before age five as compared to those mothers who are house wives. This finding was consistent with [29].

In addition, economic status of the household was also one of the socio-economic factors that are included in this study. Results in Table 8indicated that under-five child mortality risk was 52.9% less likely from children of rich mothers as compared to children of poor mothers. This is quite expected; under-five mortality for the poor family is higher than that of the rich family [29, 33]. It is believed that wealthier families can provide better nutrition, shelter and health services to their children, which intern can enhance young children's survival.

Table 8 revealed that average birth interval was found to be statistically significant effect on under-five mortality. Women with a short birth interval between two pregnancies have insufficient time to restore their nutritional reserves, which might affect foetal growth. The findings of this study showed that mothers who have average birth interval time greater than or equal to two years were at a lower risk of experiencing under-five deaths than those who have average birth interval time of less than two years. The risk of under-five mortality for those children whose mothers average birth interval time is greater than or equal to two were 78.4% less as compared to those who have average birth interval time less than two years. Similar findings were obtained by [34, 35, 30].

Table 8showed that children of mothers whose average breast-feeding time is two and higher have a significantly lower under-five deaths than children of mothers whose average breast-feeding time is lower than two. Hence, the risk of under-five mortality for those children who are fed with their mothers' breast for two years and above were 74% less likely than mothers whose average breast-feeding time is less than two years by keeping all other factors constant. Similar findings were obtained by [36]. It is recognized that mother's milk provides protection against gastro intestinal and respiratory diseases, it also meets children's nutritional requirements.

The second set of coefficients on Table 9predicts the dichotomous outcome of group membership. Only residence, kebele of mother, prenatal care, average birth interval and average breast feeding were found to be statistically significant predictors of these dichotomous outcomes.

Place of residence was found to be a significant factor for under-five child mortality. The odds of experiencing under-five mortality for those women residing in urban area were 91% less likely of those women residing in rural areas. This result is similar with [37].

The results of always zero group revealed that the odds of under-five mortality in Masero-demb, Kokora and Kembew were 13.36, 5.45 and 3.34 times more likely than among under-five deaths in Sanja respectively.

As an indicator of health care service utilization during pregnancy, prenatal care service factors demonstrated a significant effect with under-five child mortality. Children born from mothers attending prenatal care have 83.7 percent lower risk of mortality than children born from mothers attending no prenatal care. Similar findings were obtained by [34]. Giving prenatal care increase the chance of under-five survival. Appropriate prenatal care can play a role by educating women and their families to recognize delivery complications that require referral to health care services to achieve a better health outcome for both mothers and children. Average birth interval was also found significant effect with under-five mortality under the category of "always zero" group. The odds of under-five mortality of average birth interval greater than and equal to two was 85 percent less likely as compared to average birth interval less than two. Lastly, average breast-feeding time was also another covariate for under-five mortality and which was found to be statistically significant. Children of mother's who feed their children for two and above two years were 92 percent less likely for under-five mortality than of mother's who feed their children for less than two years.

Conclusion

The study has empirically examined and distinguished the factors that have significant effect on under-five mortality in Tach-Armachiho district. In this study, it was found that ZIP and ZINB regression models were better fitted the data than Poisson and negative binomial regression models. Moreover, the zero-inflated Poisson model was better fitting to the data, which is characterized by excess zeros and low variability in the non-zero outcomes. The source of overdispersion for this data was originated from the inflation of zeros and there exists low heterogeneity of not always zero-group values.

Fitting zero-inflated Poisson regression model, it was found that the factors like average birth interval and average breast feeding were found to be statistically significant factors in both groups (not always zero category and always zero category) with under-five child deathwhereas education of husband, source of water, place of delivery, mother occupation and wealth index of the household have significant effect on under-five mortality under not always zero group. Place of residence, kebele of mother and prenatal care have a significant effect on under-five mortality in Tach-Armachiho district on inflated group.

Limitations of the Study

The data used in this study was primary data of woman aged from 15-49 years. Only surviving women were interviewed; therefore, no data were available for children if their mother had died. Although many factors affect under-five mortality as indicated by different studies in different countries. This study was undertaken to explore some covariates only this is because of cross-sectional nature of our analysis and most variables were time varying covariates.

Abbreviations

AIC Akaike Information criteria
BIC Bayesian Information criteria
EDHS Ethiopian Demographic and Health Survey
LRT Likelihood Ratio Test
NB Negative Binomial
NBRM Negative Binomial Regression Model
PRM Poison Regression Model
U5D Under-five Death
U5MR Under-five Mortality Rate
UN United Nation
UN-DESA United Nations Department of Economic and Social Affairs
UNICEF United Nations International Children's Emergency Fund
ZINB Zero Inflated Negative Binomial
ZIP Zero Inflated Poisson

References

1. Unicef. (2014). The World Bank, United Nations. Levels & Trends in Child Mortality Report 2014: Estimates Developed by the UN Inter-agency Group for Child Mortality Estimation.
2. UN.(2011). Mortality estimates from major sample surveys: towards the design of a database for the monitoring of mortality levels and trends, New York.
3. UNICEF. (2007). Water and Sanitation: Frequently Used Numbers for Water and Sanitation. Facts on Children. Press Center..
4. Save the Children. (2014). State of the World's Mothers 2014: Saving mothers and children in humanitarian crises.
5. Unicef. (2015). Committing to child survival: a promise renewed. eSocialSciences.
6. UNICEF. (2013). Levels and trends of child mortality: 2013 report. Estimates Developed by the UN Inter-agency Group for Child Mortality Estimation. New York: UNICEF, WHO, World Bank, United Nations Population Division.
7. Federal Democratic Republic of Ethiopia Ministry of Health. (2014). Health sector development Programme IV: annual performance report 2012/2013.
8. DFID Ethiopia.(2011). Helpdesk Report under-five Mortality Ethiopia: DFID human development resource center.
9. Akalu, B. (2013). Child Mortality MDG Success: A signal of transformation from economic growth to development in Ethiopia.
10. UNICEF, & World Health Organization. (2015). Levels & trends in child mortality estimates developed by the UN Inter-Agency Group for Child Mortality Estimation.
11. Yimer, M., Abera, B., &Mulu, W. (2014). Soil transmitted helminths and Schistosoma mansoni infections in elemen-

tary school children at Tach Armachiho district, North-west Ethiopia. J Appl Sci Res, 2(2), 43-53.
12. Central Statistical Agency (Ethiopia).(2011). Report on livestock and livestock characteristics (prevent peasant holdings) Agricultural sample survey 2010/11, 2: statistical bulletin 505, Addis Ababa.
13. CSA, E. (2013). Population projection of Ethiopia for all regions at wereda level from 2014–2017. Central Statistical Agency of Ethiopia.
14. Cochran, W. G. (1977). Sampling techniques. John Wiley & Sons.
15. Johanson, G. A., & Brooks, G. P. (2010). Initial scale development: sample size for pilot studies. Educational and psychological measurement, 70(3), 394-400.
16. Eurostat. (2013). Handbook on precision requirements and variance estimation for European Statistical System households surveys, 2013 edition.
17. Turner, A. G. (2003). Sampling Strategies: Expert Group Meeting to Review the Draft Handbook on Designing Household Sample Surveys. United Nations Secretariat, Statistics Division: ESA/STAT/AC. 93, 2.
18. Shankar, V., Mannering, F., & Barfield, W. (1995). Effect of roadway geometrics and environmental factors on rural freeway accident frequencies. Accident Analysis & Prevention, 27(3), 371-389.
19. Cameron, A. C., & Trivedi, P. K. (2013). Regression analysis of count data (Vol. 53). Cambridge university press.
20. Cox, D. R. (1983). Some remarks on overdispersion. Biometrika, 70(1), 269-274.
21. Lawless, J. F. (1987). Negative binomial and mixed Poisson regression. The Canadian Journal of Statistics/La Revue Canadienne de Statistique, 209-225.
22. Ladron de Guevara, F., Washington, S. P., & Oh, J. (2004). Forecasting crashes at the planning level: simultaneous negative binomial crash model applied in Tucson, Arizona. Transportation Research Record, 1897(1), 191-199.
23. McCarthy, P. S. (2002). Public policy and alcohol related crashes among older drivers. In Proceedings International Council on Alcohol, Drugs and Traffic Safety Conference (Vol. 2002, pp. 3-8). International Council on Alcohol, Drugs and Traffic Safety.
24. Lambert, D. (1992). Zero-inflated Poisson regression, with an application to defects in manufacturing. Technometrics, 34(1), 1-14.
25. Heilbron, D. (1989). Generalized linear models for altered zero probabilities and overdispersion in count data. Unpublished Technical report, University of California, San Francisco, Department of Epidemiology and Biostatistics.
26. Scott Long, J. (1997). Regression models for categorical and limited dependent variables. Advanced quantitative techniques in the social sciences, 7.
27. Yau, Z. (2006). Score tests for generalization and zore-inflation in count data modeling. Unpublished Ph. D. Dissertation, University of South Caroline, Columbia.
28. Mondal, M. N. I., Hossain, M. K., & Ali, M. K. (2009). Factors influencing infant and child mortality: A case study of Rajshahi District, Bangladesh. Journal of Human Ecology, 26(1), 31-39.
29. Lemani, C. (2013). Modelling covariates of infant and child mortality in Malawi (Master's thesis, University of Cape Town).
30. Buwembo, P. (2010). Factors associated with under-5 mortality in South Africa: Trends 1997-2002 (Doctoral dissertation, University of Pretoria).
31. Muluye, S., &Wencheko, E. (2012). Determinants of infant mortality in Ethiopia: A study based on the 2005 EDHS data. Ethiopian Journal of Health Development, 26(2), 72-77.
32. Adepoju, A. O., Akanni, O., &Falusi, A. O. (2012). Determinants of child mortality in rural Nigeria. World Rural Observations, 4(2), 38-45.
33. Boco, G. A. (2010). Individual and community level effects on child mortality: an analysis of 28 demographic and health surveys in Sub-Saharan Africa. ICF Macro.
34. Singh, R., & Tripathi, V. Maternal factors contributing to under-five mortality at birth order 1 to 5 in India: A comprehensive multivariate study. SpringerPlus 2013; 2: 284.
35. Hong, R., &Hor, D. (2013). Factors associated with the decline of under-five mortality in Cambodia, 2000-2010: Further analysis of the Cambodia Demographic and Health Surveys. Calverton: ICF International.
36. Mustafa, H. E., &Odimegwu, C. (2008). Socioeconomic determinants of infant mortality in Kenya: analysis of Kenya DHS 2003. J Humanit Soc Sci, 2(8), 1934-7227.
37. Adedini, S. A. (2013). Contextual Determinants of Infant and Child Mortality in Nigeria, an unpublished PhD Thesis. University of the Witwatersrand, Johannesburg, South Africa.

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