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Count regression modelling of under-five child mortality in SNNPRS, Ethiopia

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Abstract
Child mortality, also known as under-five child mortality refers to the death of infants and children under age of five. The objective of this study was to identify the determinants of under-five child mortality among married women in SNNPRS, which is one of the nine regions in the country, Ethiopia. The data used in this study was taken from 2011 Ethiopia Demographic and Health Surveys (EDHS, which was conducted by Central Statistical Agency (CSA). The total number of mothers from SNNPRS included in the survey was 1614. In terms of AIC, Vuong's and likelihood-ratio test, ZINB regression model is better than other count models to predict the probability and determinants of the number of child death. The influences of some demographic, environmental and socioeconomic factors on child death were identified. The results show that among socioeconomic determinants: mother's educational level, household size, number of under-five children in household, mother's working status and wealth status of household are the most important determinants for child mortality. Other most important variables which were found to be statistically significant with under-five child mortality are current age of mother, mother age at first birth and type of toilet facility. Among variables included in zero-inflated part of count models, mother educational level, mother's age at first birth, wealth index and mother's working status were found to be statistically significant factors for mother's who have not experienced under-five child mortality in her life time.

Keywords: U5CD, SNNPRS, count models

Introduction

Background of the Study

Child mortality is defined as the likelihood for a child born alive to die between its first and fifth birthday. It is one of the most sensitive and commonly used indicators of the social and economic development of a population.

Globally, according to the UN Interagency Group on Child Mortality Estimation (2011) [5] a significant amount of progress has been made towards achieving the target of reducing mortality rate by two thirds among children under five. For instance, the number of under-five deaths worldwide has declined from more than 12 million in 1990 to 7.6 million in 2010. However, the highest rates of child mortality are still in Sub-Saharan Africa-where 1 in 8 children dies before the age of 5 years, more than 20 times the average for industrialized countries (1 in 167) and South Asia (1 in 15) despite action plans, interventions and broad approaches toward improving child's health in the region (WHO, 2005) [6].

UNICEF considers the child mortality rate to be a basic measure of a country's advancement. In 2004 the Ethiopian government prepared child survival strategy and implementation plan to reduce under-five mortality of 140/1000 live births to 67/1000 live births by 2015, this means a reduction of two-thirds of from the 1990 rates about 200/1000 live births or a 52 percent reduction from 2004 rate about 140/1000 live births (FMOH, 2012/2013) [7].

A number of studies indicated that the mortality rate especially the mortality rate of children under five in Ethiopia has been declining [1] and [2]. The critical forces for this decline are many. The declining of the role of agriculture in the national economy, the increase of urbanization and the launching of globalization which has accelerated the economic performance of the country and significantly changed the trend of mortality rates particularly the mortality rate of children under five [3].

The current mortality rate of children under-five is still high in comparison to the expectation of the Millennium Development Goals (MDGs). Reducing the mortality rate of children to 67 per 1000 live births was internationally adopted at the 1990 world summit for children. At this time the level of infant and child mortality rate were among vital indicators of the levels of socioeconomic progress of countries. Children are at greater risk of dying before age five if they are born in rural areas, poor households, or to a mother denied basic education [4].

It shows that, despite good achievements, Ethiopia still has high under-five mortality rate. It is still higher than the target of under-five mortality rate of 67 deaths per 1,000 live births which Ethiopian government has committed it. Therefore, progress on child mortality in Ethiopia needs continuous attention.

Statement of the Problem

Researchers on child health agree that the cause of childhood morbidity and mortality in developing countries is multi-factorial. The child's morbidity depends on the interaction of socio-economic, biological, behavioural and environmental factors (Mosley and Chen, 1984) [8].

It is not well understandable that why infant and child mortality rates are staying high and far from the desire in Ethiopia, despite the intervention target made. Researchers suggested that like other sub-Saharan region, the impact of HIV/AIDS epidemic (Rutstein, 2000) [9], poverty and economic crises contributed to the worsened of the levels of mortality particularly for infant and child mortality. It was noticed that for the decline of infant and child mortality achievement was through the intervention of disease oriented program, in recent decades the awareness of maternal, environmental, behavioural and socioeconomic factors were increased and recognized as additional important factors of infant and child mortality. At the same time the level of infant and child mortality rate are among a vital indicators used as a measurement for socio-economic progress of the country.

This study examined the causes for the increase of infant and child mortality and identified the most important factors associated with it.

Objectives of the study

General objective

The main objective of the study was to identify the determinants of under-five child death per married woman in SNNPRS using count regression models.

Specific objectives

1. To check whether the data contains over-dispersed and zero-inflated cases.
2. To assess the factors those which are statistically significant effect with under-five child mortality in SNNPRS.
3. To identify the best count regression models for prediction of under-five child death.

Data source and methodology

Data sources

The data for this study were obtained from the 2011 Ethiopia Demographic and Health survey (EDHS) conducted in Ethiopia as part of the worldwide demographic and health survey project. The survey collected Demographic and health information from a nationally representative sample of women in the reproductive age group 15-49. The survey was conducted by the Central Statistical Authority (CSA). The survey included 1614 women from SNNPRS, and the total 1129 children had been died.

Study area

The SNNPR is one of the nine regions in Ethiopia and located in the south western part of Ethiopia and shares boundaries with Kenya to the south and Sudan to the west and southwest, the regional state of Gambella Peoples' in the North west, and the regional State of Oromiya in the North and East. The area covers 110 931.9 square kilometres, which is 10% of the area of the country (SNNPR 2010). The region has 13 zones, subdivided into 126 woredas (districts), which are further divided into 3 714 rural and 238 urban sub-woredas.

Variables included in the study

Dependent variable

The response variable of this study, y_j, was a count, which gives the number of deaths of children aged under five years that each mother had experienced in her lifetime. Thus, y_j takes on values, $y_j = 0, 1, 2, \ldots,$ where j denotes the individual mother.

Independent variables

The most important socio-economic, environmental and demographic factors that determined the number of under-five child mortality were included in this study. These factors include: marital status, birth order of the child, preceding birth interval, maternal educational level, household size, place of residence and sex of the child, age of the mother at first birth, number of children born to a mother, religion, source of drinking water, access to sanitation facilities, quality of water, and access to radio, maternal health, duration of breast feeding and household income. This study focused on how these factors effect on under-five child mortality.

Children ever born and child deaths

For this study the individual women who had at least one child by the time of a census was included. Since we focused on mothers to evaluate child mortality, the exposure variable is the total number of children ever born by individual mothers

Child death counts for individual mothers were employed as the dependent variable. To manage the effects of fertility (children ever born), this factor is included as control variable.

Table 1: Description of socio-economic, environmental and demographic variables related to under-five child mortality

Variables	Categories
Highest educational level (EDULEV)	0=No education 1=Primary education 2=Secondary education
Toilet facility	1=Yes 0=no
Respondent current working status (RESWORK)	0=No 1=Yes
Wealth index (WEALTHIN)	0=Poor 1=Medium 2=Rich
Type of place of residence (RESIDENCE)	0=Urban 1=Rural
Mother age at first birth	0=Less than 20 1=20 and above
Current age of mother in years (AGE5G)	0=Less than 25 1=25-34 2=35-49
Number of household members	0=Less than 6 1=6-9 2=10 and above
Number of 5 and under five child in household (NU5CH)	0=Less Than Three 1=Three And Above
Current marital status (MARITAL)	0= Others (divorced and widowed) 1=Married
Lo Religion (RELIGION)	0=Christian 1=Muslim 2=Others

Generalized Linear Models

Generalized Linear Models (GLM) was first introduced by Nelder and Wedderburn (1972) [10]. They provided a unified framework to study various regression models, rather than a separate study for each individual regression model. Generalized linear models are extensions of classical linear models.

Statistical Models

In this section, detail description of some count regression models; mainly, Poisson, negative binomial, zero-inflated

Poisson and zero-inflated negative binomial regression models to fit under-five child death per married women will be defined.

Poisson Regression Model

Poisson regression analysis is a technique which allows for modelling dependent variables that describe count data (Cameron et al., 1998) [11].

Let $y_1, y_2, \dots, y_n$ be random variables with y_i denoting the number of U5CD from the i^{th} mother. Assume that a discrete random variable y follows a Poisson distribution with intensity or rate parameter μ, $\mu > 0$, then its density function i
s given as follows:

$$P(Y = y) = \frac{e^{-\mu}\mu^{y}}{y!}, \qquad y = 0, 1, 2 \dots$$

Where $\mu = E[y]$, the expected value of y equals the variance $V(y) = \mu$. Equality of the mean with the variance is the equi-dispersion property of the Poisson regression model. To proceed, we assume that for each individual mother, the probability of her children dying depends on the number of children exposed to the risk of mortality, hence children ever born. This then allows us to control the number of children exposed to the risk for a given woman, which we call an offset.

An offset term enters into count models as the natural logarithm of the variable which expresses the different exposure duration or times for each observation corresponding to the dependent variable in a count model. In this study, therefore, the logarithm of total number of children ever born to a mother is introduced in the regression model as an offset variable.

Consider k explanatory variables such as $x_1, x_2, \dots, x_k$, then the expected value of y_i can be written as: $E(y_i) = N_i exp\left(\beta_0 + \sum_{j=1}^{k} \beta_j x_{ij}\right)$. Taking natural logarithms, this is equivalent to:

$$\log(\mu) = \log(N_i) + \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij}$$

Where β is a $k+1$ dimensional parameter vector affecting under-five child mortality and $\exp\left(\beta_0 + \sum_{j=1}^{k} \beta_j x_{ij}\right)$ is the level and risk of the ith mother.

Let x be a $n \times (k+1)$ matrix of explanatory variables. The relationship between y_i and $\mathrm{i^{th}}$ row vector of x, x_i, linked by $g(\mu_i)$ is given by:

$$\log(\mu_i) = x_i'\beta, \text{ where } \mu_i = exp(x_i'\beta); \ i = 1, 2, \dots, n$$

With this equation, the Poisson model assumes that the mean and the variance of the outcome variable are equal. This is called equidispersion.

Negative Binomial Regression Model

The Negative Binomial (NB) regression model is an extension of the Poisson regression model that allows for an over-dispersion parameter. The negative binomial distribution is a mixture of Poisson distributions which allows the Poisson mean μ to be distributed as Gamma distribution.

Negative binomial distribution is given by**:**

$$P(Y_i = y_i / x_i) = \frac{\Gamma(\theta + y_i)}{\Gamma(y_i + 1)\Gamma(\theta)} \left[\frac{\mu_i}{\mu_i + \theta}\right]^{y_i} \left[1 - \frac{\mu_i}{\mu_i + \theta}\right]^{\theta}$$

Clearly, the negative binomial distribution approaches a Poisson distribution when θ tends to ∞ (no overdispersion).

Zero-inflated Poisson Regression

This model was first proposed by Lambert (1992) [12] with an application to defects in a manufacturing process. Zero-inflated Poisson regression is used to model count data that has an excess of zero counts. Further, theory suggests that the excess zeros are generated by a separate process from the count values and that the excess zeros can be modelled independently. Thus, the ZIP model has two parts, a Poisson count model and the logit model for predicting excess zeros.

In Zero-inflated Poisson regression model, the response variables $y = (y_1, y_2, \dots, y_n)$ are independent distributed with probability P the only possible observation is 0, and with probability, $1 - P$, a Poisson(μ) random variable is observed in y. Thus, the occurrence of y_i follows the following distributions:

$$P(Y_i = y_i) = \begin{cases} P_i + (1 - P_i)e^{-\mu_i}; & \text{when } y_i = 0 \\ (1 - P_i)\dfrac{e^{-\lambda_i}\mu_i^{y_i}}{y_{i!}}; & \text{when } y_i = 1, 2, \dots \end{cases}$$

The mean and variance of ZIP distribution are given:

$E(y_i) = (1 - P_i)\lambda_i$ and $V(y_i) = \mu_i(1 - P_i)(1 + P_i\mu_i)$.

Note that the ZIP distribution approaches to Poisson(μ) as $P \to 0$. The Poisson mean vector $\mu = (\mu_1, \mu_2, \dots, \mu_n)$ has the canonical link $\log(\mu)$ for a Poisson regression model which satisfies,

$$\log(\mu_i) = x_i'\beta, \ \Rightarrow \mu_i = \exp(x_i'\beta), \ i = 1, 2, \dots, n$$

The canonical link function is also considered for the parameter vector $P = P_1, P_2, \dots, P_n$ in ZIP regression model. That is,

$$\text{logit}(P_i) = \log\left(\frac{P_i}{1 - P_i}\right) = g_i'\gamma \ \Rightarrow P_i = \frac{e^{g_i'\gamma}}{1 + e^{g_i'\gamma}} \text{ and } 1 - P_i = \frac{1}{1 + e^{g_i'\gamma}}$$

Here x_i and g_i are explanatory variables. The explanatory variable x_i is responsible for Poisson outcome variable in y and the explanatory variable g_i is responsible for excess zeros in y. Also x_i and g_i can be identical, or may have some common covariates depending on the types of the study.

Zero-inflated Negative Binomial Regression Model

The Zero-inflated negative binomial distribution is a mixture distribution, similar to ZIP distribution, where the probability p for excess zeros and with probability $(1-p)$ the rest of the counts followed negative binomial distribution.

The ZINB distribution is given by:

$$P(Y_i = y_i) = \begin{cases} P_i + (1-P_i)\left(1+\frac{\mu_i}{\theta}\right)^{-\theta}; & y_i = 0 \\ (1-P_i)\frac{\Gamma(y_i+\theta)}{y_i!\Gamma(\theta)}\left(1+\frac{\mu_i}{\theta}\right)^{-\theta}\left(1+\frac{\theta}{\mu_i}\right)^{-y_i}; & y_i = 1,2,\ldots \end{cases}$$

The mean and variance of the ZINB distribution are $E(Y) = (1-P_i)\mu_i$ and $V(Y) = (1-P_i)\mu_i(1-P_i\mu_i + \mu_i/\theta)$, respectively. It is to be noted that this distribution approaches the ZIP distribution and the negative binomial distribution as $\theta \to\infty$ and $P_i \to 0$, respectively. If both $1/\theta$ and $p \approx 0$ then ZINB distribution reduces to Poisson distribution.

The ZINB regression model relates P_i and μ_i to covariate matrix x and g with regression parameters β and γ, respectively, as:

$$\log(\mu_i) = x_i'\beta \text{ and } \operatorname{logit}(P_i) = \log\left(\frac{P_i}{1-P_i}\right) = g_i'\gamma; \quad i = 1,2,\ldots,n$$

Comparison of the count data Models

There are many measures that can be used for estimating how well the model fits the data. After fitting Poisson regression, negative binomial regression, ZIP regression and ZINB regression model to the data, we can ask the question: what is the best model for the analysis? As a response, many tests are developed. They fall into three groups. First, there are statistics for indicating the likelihood level model, that is, how well the model maximizes the likelihood function. Among these statistics this study focused on the following tests.

Likelihood-ratio test (LRT)

The LR test is a measurement of the ratio between the likelihood under the null hypothesis and the likelihood without the null hypothesis. It is calculated as follows:

$$LR = -2\log\left(L_{H_0}/L\right) = 2[(\log L) - \log\left(L_{H_0}\right)]$$

Thus, it is twice the difference between the log likelihood functions under the full model and reduced model. This statistic has a χ^2-distribution with $K-1$ degrees of freedom, where K is number of parameters to be estimated (Oya, 1997).

To assess the model fitness and comparison, a likelihood-ratio test can be used. In order to present the results from the ZIP and ZINB models on a convenient scale, we reported the incidence rate ratio (IRR) as the rate of change in the outcome or incidence.

Akaike Information Criterion

The Akaike Information Criterion (AIC) is a way of selecting a model from a set of models. This measure also uses the log-likelihood, but add a penalizing term associated with the number of variables. It is well known that by adding variables, one can improve the fit of models. Thus, the AIC tries to balance the goodness-of-fit versus the inclusion of variables in the model. It's based on information theory, but a heuristic way to think about it is as a criterion that seeks a model that has a good fit to the truth but few parameters. It is defined as:

$$AIC = -2[\ln(\text{likelihood})] + 2k$$

Where likelihood is the probability of the data given a model and k is the number of unknown parameters in the model. Smaller values of AIC indicates a better fit.

Bayes Information Criterion (BIC)

Similar to the AIC, the Bayes information criteria also employs a penalty term associated with the number of parameters (*K*) and the sample size (*n*). This measure is also known as the Schwarz Information Criterion. It is computed by the following way:

$$BIC = -2\ln L + P\ln L\, n$$

Similarly, smaller value of BIC indicates that a given model fitted the data better.

Deviance

The deviance is a measure of goodness of fit that can be used to assess models. It is defined as twice the difference between the maximum likelihood achievable and the likelihood of the fitted model. It is computed as follows:

$$D(y,\mu) = 2\{L(y) - L(\hat{\mu})\},$$

Smaller values of the deviance indicates that the model fits the data better.

Vuong's Test

Vuong test is a test statistic used to select inflated models over standard models. To define the Vuong test (V), suppose $P_1(y_i,x_i)$ and $P_2(y_i,x_i)$ denote the probability density function of zero-inflated model (ZIP or ZINB) and standard model (Poisson or Negative Binomial), respectively; and $F_1(y_i,x_i)$ and $F_2(y_i,x_i)$ denote their corresponding cumulative distribution functions. We want to test the following hypothesis:

H_o: Two distribution functions are equivalent

H_A: Two distribution functions are different (two tail test)

Now we define,

$$m_i = \log\left(\frac{\hat{P}_1(y_i/x_i)}{\hat{P}_2(y_i/x_i)}\right)$$

Where $\widehat{P_1}(y_i,x_i)$ and $\widehat{P_2}(y_i,x_i)$ are predicted probabilities of the corresponding models $P_1(y_i,x_i)$ and $P_2(y_i,x_i)$ respectively. Let $\overline{m} = \frac{1}{n}\sum_{i=1}^{n} m_i$ and $s_m = \sqrt{\frac{1}{n-1}\sum_{i=1}^{1}(m_i - \overline{m})^2}$ denotes the mean and standard deviation of the measurements, respectively, m_i. Then the Vuong test statistic is defined as,

$z = \bar{m} / (s_m/\sqrt{n})$

Reject H_0 if the Z-value is greater than critical value ($Z\alpha/2$) and significant, then ZIP and ZINB are better fit than the standard Poisson and NB respectively.

Results and Discussions

In this chapter, discussions of findings and summary of results be presented.

Descriptive statistics

The distribution of the number of under-five child mortality per married mother and the cross tabulation of U5CD by explanatory variables is the subsequent task in this section.

Table 2: Frequency distribution of mothers that experienced U5CDs.

U5CD	Frequency	Percent	Cumulative percent
0	952	58.98	58.98
1	378	23.42	82.40
2	175	10.84	93.25
3	58	3.59	96.84
4	33	2.04	98.88
5	13	0.81	99.69
6	5	0.31	100.00
Total	1,614	100.00	

Table 2 show the summery of under-five child death of 1614 women of SNNPRS surveyed in EDHS 2011. It can be seen that approximately 59% of the mothers have not faced any U5CD in their life time; nearly 23.42% of mothers in SNNPRS have experienced one event of under-5 death in their reproductive age, whereas 0.31% of them faced six U5CD. The data seems to be a good candidate to be fitted by zero-inflated count data models because nearly 59% of the women never experienced under-5 death of their children. The overall pattern of U5CD at the regional level shows a pattern which is highly skewed to the right with excess zeroes.

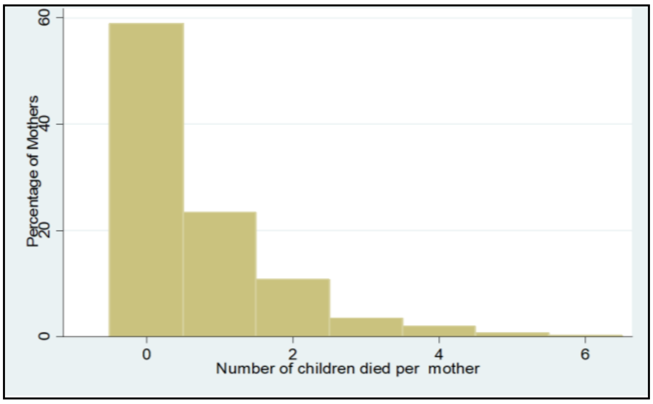

Fig 1: Histogram for count of under-five child death per mother.

Table 3: Summary statistics for number of under-five child death

Variable	Obs	Mean	Std. Dev.	Min	Max
U5CD	1614	.6995043	1.068996	0	6

Table 3 show that the mean number of children died per mother was 0.6995 and the variance was 1.143, a bit more than the mean. The data were an indication of over-dispersion.

Comparisons of models

Residuals by count models

Table 4: Predicted and actual probabilities of U5CD by count regression models

		Poisson model			NB model		
Count	Actual	Predicted	|Diff|	Pearson	Predicted	|Diff|	Pearson
0	0.590	0.560	0.030	2.522	0.581	0.009	0.202
1	0.234	0.274	0.040	9.460	0.255	0.021	2.733
2	0.108	0.105	0.004	0.190	0.097	0.011	2.094
3	0.036	0.039	0.003	0.283	0.038	0.002	0.194
4	0.020	0.014	0.006	4.483	0.016	0.005	2.236
5	0.008	0.005	0.003	2.637	0.007	0.001	0.330
6	0.003	0.003	0.001	1.483	0.003	0.000	0.000
Sum	1.000	1.000	0.087	22.429	1.000	0.051	11.686
		ZIP model			ZINB model		
0	0.590	0.588	0.001	0.006	0.584	0.006	0.091
1	0.234	0.234	0.000	0.000	0.247	0.013	1.049
2	0.108	0.107	0.001	0.022	0.101	0.007	0.770
3	0.036	0.044	0.008	2.235	0.040	0.004	0.719
4	0.020	0.017	0.004	1.178	0.016	0.004	1.912
5	0.008	0.006	0.002	0.781	0.007	0.001	0.539
6	0.003	0.002	0.001	0.513	0.003	0.000	0.078
Sum	1.000	1.000	0.018	6.498	1.000	0.038	8.141

In Table 4 we were able to see, for counts 0-6, the actual proportion of our data records with the given count and the predicted proportion from each model. The absolute difference was included, as is the given count's contribution to a Pearson chi-square statistic comparing the actual distribution of the data and the distribution proposed by the model.

The result in table 4 showed that approximately 59% of the SNNPRS women were included in EDHS had not experienced under-five child death in their life time, and around 23%, 10%, 3.6%, 2%, 0.8% and 0.3 of women had lost one to six children in their life time, respectively. But the Poisson model predicts that only 56.9% would not experience under-five child death where as the remaining 27%, 10.5%, 3.9%, 1.4%, 0.5%, 0.3% of women had lost one to six children in their life time, respectively. Clearly, the Poisson model underestimates the probability of zero, four and five counts and overestimate one, two and three counts.

The negative binomial distribution predicts 58% of women in SNNPRS included in EDHS survey had not lost their child. The remaining 25.5%, 9.7% and 3.8% of women lost one up to four children in their life time. But only 1% of women have experienced more than four under-five child mortality. It under estimated zero counts and overestimated some of positive counts and overestimates the rest counts.

Looking at the sum of the Pearson column gives us a sense of how close the predicted proportions were to the actual proportions. Using this method to compare, the ZIP model appears better than the others. It was worth visualizing the comparison between the observed counts and the predicted counts from the Poisson model, negative binomial, ZIP and ZINB models. Figure 4.1 provided that points above 0 on the y-axis indicated more observed counts than predicted and those below 0 indicated more predicted counts than observed.

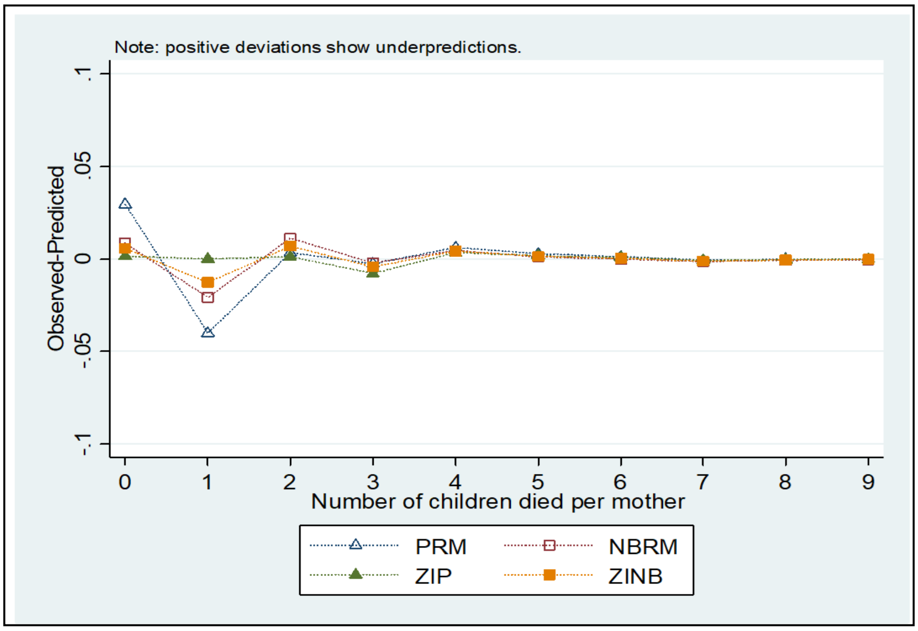

Fig 2: Comparison between observed and predicted counts from four count models

Figure 3.2 performed that the plots of the residuals from the tested models. Small residuals were an indication of good-fitting models, so the models with lines closest to zero should be considered for U5CD.

Figure 3.2 showed that the ZIP model predicted the zero and one count almost perfectly while Poisson, NB and ZINB under estimate zero count and overestimate one count.

Summary of comparisons

To compare the performance of Poisson versus ZIP and NB versus ZINB we used Vuong's test statistic since the models are non-nested (Vuong's, 1989) [13].

Table 4, the tested models were compared to each other head-to-head using the test statistic appropriate to each comparison. Each line can be boiled down to the last three columns. They suggested which model was preferred by the given comparison and the strength of the evidence supporting this preference.

The result also showed that the ZIP and ZINB regression model is actually the best model which fit the under-five mortality data because the Vuong's test showed that the ZIP and ZINB models are the better fit than the standard Poisson and negative binomial model, respectively.

Table 5: Tests and fit statistic

PRM		BIC= 3383.978	AIC=3313.953	Prefer	Over	Evidence
Versus	NBRM	BIC= 3372.379	dif=11.598	NBRM	PRM	Very strong
		AIC= 3296.969	dif=16.985	NBRM	PRM	
		LRX^2= 18.985	prob=0.000	NBRM	PRM	p=0.000
Versus	ZIP	BIC= 3409.022	dif=-25.044	PRM	ZIP	Very strong
		AIC= 3290.519	dif=23.434	ZIP	PRM	
		Vuong= 3.290	prob=0.001	ZIP	PRM	p=0.001
Versus	ZINB	BIC= 3402.285	dif=-18.307	PRM	ZINB	Very strong
		AIC= 3278.396	dif=35.557	ZINB	PRM	
NBRM		BIC= 3372.379	AIC=3296.969	Prefer	Over	Evidence
Versus	ZIP	BIC= 3409.022	dif=-36.642	NBRM	ZIP	Very strong
		AIC= 3290.519	dif=6.449	ZIP	NBRM	
Versus	ZINB	BIC= 3402.285	dif=-29.906	NBRM	ZINB	Very strong
		AIC= 3278.396	dif=18.573	ZINB	NBRM	
		Vuong= 3.044	prob=0.001	ZINB	NBRM	p=0.001
ZIP		BIC= 3409.022	AIC=3290.519	Prefer	Over	Evidence
Versus	ZINB	BIC= 3402.285	dif=6.737	ZINB	ZIP	Strong
		AIC= 3278.396	dif=12.123	ZINB	ZIP	

		LRX^2= 14.123	prob=0.000	ZINB	ZIP	p=0.000

When we compared our tested models using AIC, the zero-inflated negative binomial was preferred over Poisson, negative binomial and ZIP models. The Vuong's test supported ZIP and ZINB models over Poisson and negative binomial models, respectively, and also both AIC and likelihood-ratio test preferred ZINB model over ZIP model at statistical significant level. Therefore, the best chosen model for under-five child mortality was ZINB regression model.

Estimates of parameters using ZINB regression Model

Table 6: Count Equation: Factor change in expected count for those not always 0

Variables and their categories	β	z	P>|z|	e^β
Mother age group (<25=ref.)				
25-34	0.3814	1.670	0.005	1.464
35-49	0.8646	3.758	0.000	2.374
Mother working status (no=ref)	0.1484	2.261	0.024	1.160
Toilet facility (other =ref)	0.1483	2.061	0.039	1.160
Mother education level (no education =ref.)				
Primary	-0.3854	-4.693	0.000	0.680
Secondary/high	-0.2537	-0.264	0.002	0.776
Number of household members (<6= ref.)				
6-9	-0.7251	-10.368	0.000	0.484
Ten and more	-0.9096	-6.984	0.000	0.403
Number of under 5 child (<3 =ref.)	-0.2854	-2.988	0.003	0.752
Wealth index (poor is ref)				
Medium	-0.1524	-1.636	0.002	0.859
Rich	-0.2488	-2.897	0.004	0.780
Mother age at 1st birth (<20yrs = ref.)	-0.3506	-4.755	0.000	0.704
Constant	-1.6835	-7.515	0.000	.
Alpha				
lnalpha	-2.9315	.	.	.
Alpha	.05332			

Table 7: Binary equation: factor change in odds of always 0.

Variables and their categories	β	Z	P>|z|	e^β
Mother age group (<25=ref)				
25-34	0.3942	0.452	0.1002	1.483
35-49	0.3963	0.79	0.064	1.486
Mother work status	-0.5380	-1.136	0.006	0.584
Mother education level				
Primary	-1.8031	-2.164	0.030	0.165
Secondary/high	0.3016	0.155	0.007	1.352
Wealth index				
Medium	0.5172	0.844	0.009	1.677
Rich	0.6160	1.052	0.003	1.852
Mother age at 1st birth	-0.4139	-0.763	0.005	0.661
Constant	-0.1285	-0.192	0.0003	

Note: Reference category for each variable are the similar with in positive count equation table. β = raw coefficient, z = z-score for test of β=0, P>|z| = p-value for z-test, e^β = exp (β) = factor change in odds for unit increase in X

We now fitted zero-inflated negative binomial regression model to analyse the risk factors under-five child mortality. The most statistically significant factors of U5CD results were given in Table 6 and 7.

The result has shown that children of mothers with primary education had approximately 32% lower risk of mortality as compared to children whose mother had no education. Children whose mothers had secondary and higher education was 23% of lower risk of death as compared with children whose mother had no education. Generally, educational level of mothers was an important and significant factor of under-five child mortality risks in SNNPRS.

It also indicated that children born from mothers whose age at first birth was greater than twenty was found statistically significant effect of lower mortality as compared to those born from mothers whose age at first birth was less than or equal to twenty. A mother who gave her first birth at age of greater than twenty years had 30% less probability to lose her child than mother who gave first birth at age below twenty years.

The result also showed that mothers who had a job were 16% more likely to have a higher number of child lost as compared to mothers who had no work.

The presence of more under-five children in the household decreases the risk of child loss. Household with three and above children was 25% less likely to loose child as compared to household with less than three children. The presence of more household member in the family had a negative effect on under-five child mortality. Household with six up to nine members and ten and more members have 52% and 60% lower child mortality as compared to household with less than five members. The child care provided by such individuals could be the reasons for these findings. It is also found that under-five child mortality risk was 14% and 22% lower for children of medium and rich household as compared to children of poor household, respectively.

The binary equation table showed that a mother was less likely to have positive counts of under-5 deaths of her children with higher level of education. The odds ratio was 0.165 that is; mothers who had primary education were 0.165 times less likely to experience under-5 deaths in comparison to a mother who had no education. On the other hand, women who had experienced under-5 deaths were more likely to belong to the uneducated group with higher number of such experience.

Conclusion and recommendation
Conclusions

This chapter deals with summary of all the findings, the conclusions drawn from the findings and suggested recommendations to reduce the under-five child mortality in SNNPRS.

This study sought to identify factors associated with under-five mortality in SNNPRS, Ethiopia. We used 2011 EDHS data and applied count regression models. Totally, 1614 mothers of the region who aged 15-49 years were included in EDHS 2011 survey to ascertain their background information. Information gathered from the mothers was grouped into socio-economic, demographic, biological and environmental factors. At the regional level, the average number of U5CD from the individual mother in her lifetime was found to be 0.699.

We have explored the determinants of under-five mortality and utilized some count models to predict under-five child mortality in the SNNPRS in Ethiopia. The results revealed that demographic, socioeconomic and environmental factors were statistically significant effect with under-five child mortality. Mothers' education level; wealth index and current age of mother, mother current working status, toilet facility, size of household, number of under-five children in household and age of mother at first birth were statistically significant effect with under-five child mortality at 5% level of significant.

With regard to socio-economic variables: the effects of mother education play an important role for the reduction of child mortality. Child mortality was highly affected with mother's educational status that increases the awareness of how to care her children before births and after births and enables her to change feeding and childcare practices by shaping and modifying the traditional familial relationships. The odds of not having under-five child mortality for mother who have primary and secondary/higher was high as compared to mothers who have no education. Mother's education enhances to improve more effective preventative and health care practice, this increase her productivity and influence child mortality. Many studies showed that the higher the level of maternal education, the lower the child mortality. In Ethiopia, Kumar and Gemechis (2010) [14] also found that child mortality lower for children born to mothers whose educational level is secondary and above relative to children born to illiterate mothers. Caldwell (1981) [15] also 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 line with study children born to mothers with secondary education level are a significant impact on reducing under-five mortality.

The presence of children aged less than five years reduces the risk in child loss, because, as the number of children in the household increases, mothers are required to provide more physical and financial support. Perhaps mothers with more children are better experienced in childbearing and possess more knowledge of childbearing practices. Similar research was conducted by Kuniko (2010) [16].

The study indicated that children born from working mothers had higher risk of mortality than non-working mothers. It was found that mothers' current age did not have significant effect on zero counts while it was found to be significant effects on positive counts.

From positive counts model it could be concluded that under-five child mortality risk is higher for children of poor household compared to children of medium and rich households. Mother's age at first birth is negatively correlated with under-five mortality that decreased the risk of under-five mortality as increase mother's age at first birth. The estimated result also showed that mother's age at first birth increases reduced the risk of child mortality. Similar findings were obtained by Desta (2011) [4] and Abdullah *et al*. (2014) [17]. Mother's current age were found to be statistically significant effects on the degree of experiencing under-5 child deaths. Increase in mother current age was associated with increase in a number of child mortality (positive counts) and it was not significant in zero counts of child death.

In this study, it was shown that the zero-inflated models, ZIP and ZINB are consistent over predicting the probability of zero counts as well as positive counts. ZINB model had a higher flexibility to fit a model with mixture of distribution for zeros and positive counts and it performed in a competitive way with ZIP.

Finally, number of under-5 deaths of a mother is a good candidate to apply zero- inflated count data models. This study have found that the zero-inflated models, specially ZIP and ZINB have better performance than the Poisson and Negative binomial models in terms of AIC and Vuong's test statistic. ZINB regression model was preferable over ZIP in terms of likelihood-ratio test and AIC. Therefore, ZINB regression model was best among four count models used in this study even if it has almost similar performance with ZIP to estimate the coefficients and standard errors.

Recommendation

Based on the results and conclusions the following recommendations were forwarded.

- Government policy should focus on the above important determinants of child survivals and health intervention policies should be implement to reduce child mortality.
- Because, educational level of mother's plays an important role in child mortality the study also suggested that encourage mothers to increase their education levels up to at least secondary levels. This shaping parental behaviour toward children and increase the awareness and capacity to manipulate health services for their children. This is, however, a

long-term investment. As an alternative, in the short term, health programs need to focus on supporting women with little or no education.
- Effective programs to reduce early childbearing of women should be implemented so as to decrease under-five child mortality.

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