Analysis of Risk Factors of Neonatal Mortality in Ethiopia using Count Data Models

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Abstract

Background: Neonatal mortality (NM) is a significant public health concern worldwide. It is estimated that four million neonatal deaths occur annually, 98% of which occur in developing countries. In Ethiopia, neonatal mortality accounts for more than 42% of under-five deaths.

Objectives: This study attempted to explore the determinants of neonatal mortality in Ethiopia based on data from the Ethiopian Demographic and Health Survey (EDHS, 2011) using count data models.

Methods: To meet our objectives, Poisson, negative binomial, zero inflated Poisson and zero-inflated negative binomial (ZINB) regression models were used for data analysis considering the number of neonatal deaths per-woman as the response variable.

Results: Our analysis revealed that ZINB model was a better fit to the data than the other models. Descriptive statistics results show that nationally 23.2% of mothers have faced at least one neonatal death in their lifetime. The results of the ZINB regression model revealed that being born to mothers whose age at first birth is at least 20 years, whose level of education is secondary and above, who reside in urban areas and who attended at least four antenatal care visits significantly decrease the risk of neonatal mortality.

Conclusion: Increasing access to maternal and child health services in rural areas, improving the level of education of mothers, and encouraging utilization of antenatal care services are some of the interventions that help to mitigate the problem of neonatal mortality.

Key words: *Neonatal Mortality, Poisson, Negative binomial, Zero-inflated Poisson, Zero-inflated Negative binomial*

1. Introduction

Neonatal period (from birth to 28th day of life) is the most vulnerable and high-risk time in life because of the highest mortality and morbidity incidence in human life during this period. Neonatal mortality (NM) refers to the incidence of death of a live born infant within the first 28 days of life. An estimated 40 percent of deaths in children less than five years of age occur during the first 28 days of life. The average daily mortality rate during the neonatal period is close to 30 fold higher than that during the postnatal period (one month to one year of age). In 2010, out of an estimated 7.7 million children under five years of age who died worldwide, 3.1 million were neonatal deaths (WHO, 2011).

Sub-Saharan Africa has the highest risk of death in the first month of life and is among the regions showing the least progress. However, it has seen a faster decline in its under-five mortality rate, with the annual rate of reduction doubling between 1990–2000 and 2000–2011. Sub-Saharan Africa, with 1.1 million neonate deaths in 2011, accounts for 38 percent of global neonatal deaths (USAID, 2012).

Approximately 42% of the under-5 mortality in Ethiopia is attributable to neonatal deaths (CSA and ICF International, 2012). According to the 2011 Ethiopia Demographic and Health Surveys (DHS), the country is experiencing a high neonatal mortality rate at 37 per 1000 live births, comparable to the average rate of 35.9 per 1000 live births for the African region overall (Oestergaard et al., 2011). Despite this fact, there are only few studies that focus on identifying and analyzing the various household, maternal and socio-demographic, socio-economic and environmental factors associated with neonatal mortality. An understanding of the factors related to neonatal mortality is important to guide the development of focused and evidence-based health interventions. Therefore, this study aims to identify possible risk factors for neonatal deaths using the 2011 Ethiopian Demographic and Health Survey data.

The study is organized into four chapters. Following the introductory chapter one, chapter two discusses the methodology and sources of data used in the study. The third chapter deals with model estimation and interpretation of results. Finally, chapter four presents conclusions and recommendations of the study.

2. Materials and Methods

2.1 Data used in the study

The data for this study are obtained from the Ethiopian Demographic and Health Survey of 2011. The principal objective of the 2011 EDHS was to provide current and reliable data on fertility and family planning, child and maternal mortality, nutritional status of children, and use of maternal and child health services, among others.

This study analyses responses from each of 9,209 women of childbearing age (15-49), and who have ever born a child, on the counts of the number of deaths of children aged less than one month that the they have encountered in their lifetime. In EDHS, information on child mortality was found from the birth history of women who were included in the survey.

2.2 Methodology

2.2.1 Introduction

In statistical analyses, response variables may be limited by being count data, only taking on nonnegative integer values. In almost all practical cases, count data are skewed, non-negative, over-dispersed and have excess zeros. These features have motivated the application of various methods and models for count data regressions. The classical linear regression is not an appropriate estimation technique for count data as it fails to take into account the limited number of possible values of the response variable. The most common technique employed to model count data is Poisson regression. One limitation of the Poisson distribution is the equality of its mean and variance. We may often observe count data processes where the conditional variance is larger than the conditional mean - termed over-dispersion. In this circumstance, a reasonable alternative is negative binomial regression. Besides the problem of over-dispersion, it is also common that real life count data exhibit excess zeroes. The Zero-inflated Poisson and Negative Binomial Regression models can be used to handle such excess zeroes.

2.2.2 Poisson regression (PR) model

Suppose $Y_1, Y_2, \ldots, Y_n$ are independent random variables. Let y_i denote the value of an event count outcome variable (neonatal death in our case) for i^{th} mother within a given time or exposure period with mean parameter λ_i and X_i denote a vector of explanatory variables for the i^{th} mother. Poisson regression is the simplest regression model for count data and assumes that each observed count y_i is drawn from a Poisson distribution with conditional mean λ_i ($Y_i \sim \text{Poisson}(\lambda_i),\ i = 1, 2, \ldots, n$) on a given vector X_i. The Poisson probability mass function with mean λ_i is given by:

$$p(Y_i = y_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!},\ \lambda_i > 0,\ y_i = 0, 1, 2, \ldots \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

The mean of the response variable λ_i is related with the linear predictor through the so called link function. Let **X** be n x (k+1) matrix of explanatory variables. The relationship between Y_i and i^{th} row vector of X (X_i), linked by the canonical link function $g(\lambda_i)$, is given by:

$$E(Y_i) = \lambda_i = \exp(X_i'\beta) \quad \ldots\ldots (2)$$

where $X_i = (x_{i0}, x_{i1}, \ldots, x_{ik})'$ is the i^{th} row of covariate matrix (with $x_{i0} = 1$) and $\beta = (\beta_0, \beta_1, \ldots, \beta_k)'$ is unknown vector of regression parameters. The model comprising Equations (1) and (2) is known as the Poisson regression or log-linear model. The log of the mean λ_i is a linear function of the independent variables, that is,

$$\ln(\lambda_i) = X_i'\beta = \beta_0 + \sum_{j=1}^{k} x_{ij}\beta_j \quad \ldots\ldots (3)$$

where x_{ij} is the i^{th} observation corresponding to the j^{th} covariate, k is the number of covariates in the model, and β_j is the j^{th} regression parameter (Cameron and Trivedi, 1998; Lawless, 1987; Agresti, 2007).

2.2.3 Negative binomial regression (NBR) model

Let $Y_1, Y_2, \ldots, Y_n$ be a set of n independent random variables where Y_i follows a negative binomial distribution with mean λ_i and dispersion parameter α (denoted by $Y_i \sim NB(\lambda_i, \alpha),\ i = 1, 2, \ldots, n$). The negative binomial model takes the form:

$$p(Y_i = y_i) = \frac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{\Gamma(y_i + 1)\Gamma\left(\frac{1}{\alpha}\right)} \left(\frac{\alpha\lambda_i}{1 + \alpha\lambda_i}\right)^{y_i} \left(\frac{1}{1 + \alpha\lambda_i}\right)^{1/\alpha},\ \lambda_i, \alpha > 0,\ y_i = 0, 1, 2, \ldots \quad \ldots\ldots (4)$$

Covariates can be introduced into a regression model based on the NB distribution via the relationship described in Equation (3) above (Cameron and Trivedi, 1998; Lawless, 1987; Agresti, 2007).

2.2.4 Zero-inflated regression models

Although the negative binomial model can solve an over-dispersion problem, it may not be well flexible to handle excess zeros. This motivates the development of Zero-Inflated count models to model excess zeros in addition to over-dispersion.

When there are excess zeros in the response variable, the problem of standard models in under-predicting zeros and over-predicting the other outcomes is very common. In such cases, zero inflated Poisson (ZIP) and zero inflated negative binomial (ZINB) models can be used to account for excess zeros. The zero values in the ZIP model can be viewed as comprising two parts. One portion of the zero counts arises from the inflated part of the distribution and the other portion comes from what would be expected given a Poisson distribution with parameter λ.

a) Zero-inflated Poisson (ZIP) regression model

The general form of the zero-inflated probability mass function is:

$$p(Y_i = y_i) = \begin{cases} \phi_i + (1-\phi_i)p(Y=0) & \text{if } y_i = 0 \\ (1-\phi_i)p(Y=y_i) & \text{if } y_i = 1, 2, \ldots \end{cases} \quad \ldots\ldots\ldots\ldots (5)$$

If Y_i 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 ϕ_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 (Cameron and Trivedi, 1998):

$$p(Y_i = y_i) = \begin{cases} \phi_i + (1-\phi_i)e^{-\lambda_i} & \text{if } y_i = 0 \\ (1-\phi_i)\dfrac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} & \text{if } y_i = 1, 2, \ldots \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

This is denoted by $Y_i \sim \text{ZIP}(\lambda_i, \phi_i),\ 0 \le \phi_i < 1$, where λ_i is the mean of the non-zero outcomes that can be modeled with the associated explanatory covariates using the natural logarithmic link function $\ln(\lambda_i) = X_i'\beta$ and ϕ_i is the probability of an excess zero (being in the zero mortality state) determined by a logit model. To predict membership in the "always- zero" group, we can use the same set of explanatory variables or we can use a smaller subset of the variables or even different variables altogether.

b) Zero-inflated negative binomial (ZINB) regression model

The main difference between ZIP and ZINB model is that the Poisson distribution for count data is replaced by the negative binomial distribution. The probability density function of a zero-inflated negative binomial distribution is a simple modification of the ZIP and is given by:

$$p(Y_i = y_i) = \begin{cases} \phi_i + (1-\phi_i)(1+\alpha\lambda_i)^{-\frac{1}{\alpha}} & \text{if } y_i = 0 \\ (1-\phi_i)\dfrac{\Gamma\left(y_i + \frac{1}{\alpha}\right)(\alpha\lambda_i)^{y_i}}{\Gamma(y_i+1)\Gamma\left(\frac{1}{\alpha}\right)(1+\alpha\lambda_i)^{y_i+\frac{1}{\alpha}}} & \text{if } y_i > 0 \end{cases} \quad \text{........ (7)}$$

where λ_i is the mean of the non-zero responses that can be modeled with the associated explanatory covariates using a natural logarithm link function as defined in Equation (3), and ϕ_i is the probability of excess zeros which can be estimated by logistic regression as defined in Equation (5) (Long, 1997).

The ZINB model is a special case of a two-class finite mixture model with mean $E(Y_i) = \lambda_i(1-\phi_i)$ and variance $Var(Y_i) = \lambda_i(1-\phi_i)(1+\alpha\lambda_i + \phi_i\lambda_i)$, where the parameters λ_i and ϕ_i depend on the covariates and $\alpha \geq 0$ is a scalar. Thus, we have over-dispersion whenever either ϕ_i or α is greater than zero. Equation (7) reduces to NB when $\phi_i = 0$ and to the ZIP when $\alpha = 0$.

2.2.5 Assessing model fit

a) Testing hypotheses for the significance of model parameters

To test whether the entire set of explanatory variables contribute significantly to the prediction of the response variable, we can use the deviance (likelihood ratio) test. The test statistic is given by (Mccullagh and Nelder, 1989):

$$D = 2\left\{\sum y_i \log\left(\frac{y_i}{\hat{\lambda}_i}\right) - y_i + \hat{\lambda}_i\right\} \quad \text{.. (8)}$$

where $\hat{\lambda}_i$ is the predicted value from the fitted regression model. Under the null hypothesis $H_0 : \beta_1 = \beta_2 = \ldots = \beta_k = 0$, D is asymptotically distributed as Chi-square with k degrees of freedom.

b) Test for over-dispersion and zero-inflation

The negative binomial regression model reduces to the Poisson regression model when the over-dispersion parameter is not significantly different from zero. To assess the adequacy of the negative binomial model over the Poisson regression model, we can test the hypothesis: $H_0 : \alpha = 0$ versus $H_1 : \alpha > 0$. The general score test statistic for testing these hypotheses is given by:

$$S_\alpha = \frac{\left[\sum_{i=1}^{n}\left\{(y_i - \hat{\lambda}_i)^2 - y_i\right\}\right]^2}{2\sum_{i=1}^{n}\hat{\lambda}_i^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

Under the null hypothesis that the data follow a Poisson model, the limiting distribution of the score statistic is Chi-square with one degree of freedom (Dean and Lawless, 1989).

The likelihood ratio test is not appropriate to compare Poisson or negative binomial with the zero inflated Poisson and negative binomial since one is not nested in the other. Vuong (1989) has introduced a test which is a well suited to compare zero-inflated regression models with standard non-nested models for counts data. Suppose $f_1(y_i | X_i)$ and $f_2(y_i | X_i)$ denote the probability density functions of zero-inflated model (ZIP or ZINB) and standard Poisson or NB model, respectively. We define m_i as:

$$m_i = \log\left[\frac{\hat{f}_1(y_i | X_i)}{\hat{f}_2(y_i | X_i)}\right] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

where $\hat{f}_1(y_i | X_i)$ and $\hat{f}_2(y_i | X_i)$ are predicted probabilities of the corresponding models. The Vuong statistic is defined as:

$$V = \frac{\bar{m}}{S_m / \sqrt{n}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

where $\bar{m}$ and S_m are the mean and standard deviation of the measurements m_i. Under the null hypothesis that the two distribution functions are equivalent, this statistic has an asymptotic standard normal distribution.

c) Goodness of-fit Tests

In this study, a likelihood ratio was used to compare the Poisson with the negative binomial and zero-inflated Poisson with zero-inflated negative binomial. The likelihood ratio statistic is given by:

$$T = 2\{\ell_1 - \ell_0\} \quad \text{...} \quad (12)$$

where ℓ_1 and ℓ_0 are model log-likelihoods under the alternative and null hypothesis, respectively. T has a Chi-square distribution with one degree of freedom.

3. Results and Discussion

3.1 Model comparison

The variable of interest in this study was the number of neonatal deaths per woman through her life time. Such data can be well fitted by count data models rather than standard linear regression models. In this study we have considered different count data models.

At the initial stage, a Poisson model was fitted to identify the risk factors of neonatal mortality. The fitted Poisson model was then tested for over-dispersion. The negative binomial model is an immediate solution in case there is over-dispersion. However, the over-dispersion might be due to excess zeroes. This brings the zero-inflated models into the picture. Thus, four different models were considered, namely: the standard Poisson, negative binomial, zero-inflated Poisson and zero-inflated negative binomial models.

The deviance-based Chi-square test results indicated that the Poisson model was a good fit to the data. However, the validity of Poisson regression analysis relies heavily on the assumption of equi-dispersion. The value of the score test statistic for over-dispersion was $\chi^2 = 1322.77$ with p-value <0.0001. This is an indication that there is over-dispersion and the standard Poisson model is inappropriate. As a natural alternative, we fit a negative binomial regression model which was found to be a good fit as judged by the deviance and Pearson's Chi-square tests.

We then fit zero-inflated negative binomial regression model and compared it with the standard NB model using Vuong test. The test result indicated that the former is a better fit to the data compared to the latter one. Moreover, the Pearson's Chi-square goodness-of-fit test statistic for the ZINB model was significant ($\chi^2 = 14144.59$, p-value <0.0001). Therefore, zero-inflated negative binomial (ZINB) regression model is the most appropriate model which fits the data better than the other possible candidate models.

3.2 Interpretation and discussion of results

Table 1 presents the results of the fitted ZINB model for predicting the mean response (λ). The coefficients can be interpreted in the same way as regular negative binomial coefficients. The factors place of residence, education level of mothers, source of water supply, religion, mothers' age at first birth, antenatal care, postnatal care and education level of husband/partner were found to be statistically significant predictors of the count outcome. On the other hand, availability of toilet facility, place of delivery and occupation of mothers were not statistically significant.

The findings of the study show that being born to a mother with secondary/higher and primary education were associated with a 64% and 32% decreased risk of neonatal mortality compared to being born to mothers with no education, respectively, keeping all other covariates constant. A study by Van Ginneken et al. (1996) also reported a negative relationship between neonatal death and maternal education. They argued that education improves the ability of mothers to implement simple health knowledge and facilitates their capacity to interact more effectively with health professionals, comply with treatment recommendations, and keep their environment clean.

The results also indicated that children born from mothers whose age at first birth was at least 20 years had a significantly lower risk of mortality compared to those born from mothers whose age at first birth was less than 20 years. The risk of neonatal death was about 25% lower for births to mothers aged 20 and above compared to those in the reference category (OR: 0.751; CI: 0.666-0.846). This finding is consistent with those of Stanton and Langsten (2000) and Hidalgo et al. (2005).

The other factor that has a significant association with neonatal mortality is place of residence. The risk of neonatal death was about 1.3 times higher for a child whose mother resided in rural areas compared to their urban counterparts. Theoretically, all things being equal, living in urban areas is associated with better sanitation and health facilities, among others. This finding is in agreement with the study conducted by Nsour et al. (2003) in Jordan.

The findings of this study revealed that mothers who use water from unprotected sources were at a higher risk of experiencing neonatal death than those who use pipe water. Lack of clean water supply combined with little or no health care knowledge can provide routes for infections. Peterson et al. (1986) also reported that access to clean water and hygienic practices reduces maternal and neonatal mortality and morbidly especially during delivery.

Table 1: Results of the fitted ZINB model ("Not Always zero" group)

Covariates	B	SE	Z	Sig.	Exp(β)	95% C. I.	
						Lower	Upper
Residence (Urban)*							
Rural	0.274	0.095	2.89	0.004	1.315	1.092	1.583
Edu. moth (No educ.)							
Primary	-0.381	0.071	-5.39	<0.001	0.683	0.595	0.785
Secondary and higher	-1.015	0.180	-5.63	<0.001	0.363	0.255	0.516
Water (Pipe)							
Protected	0.117	0.081	1.44	0.15	1.124	0.958	1.318
Unprotected	0.209	0.072	2.88	0.004	1.232	1.069	1.420
Toilet (No facility)							
With facility	-0.083	0.064	-1.31	0.19	0.920	0.812	1.042
Religion (Orthodox)							
Protestant	0.275	0.100	2.76	0.006	1.317	1.083	1.602
Muslim	0.204	0.077	2.61	0.009	1.226	1.052	1.428
Age moth. (< 20)							
20 and above	-0.287	0.078	-4.72	<0.001	0.751	0.666	0.846
ANC (No visits)							
1-3 visits	-0.223	0.086	-2.61	0.009	0.800	0.676	0.946
4 or more visits	-0.387	0.084	-4.58	<0.001	0.679	0.575	0.801
Pl. del. (Home)							
health facility	-0.110	0.111	-0.99	0.322	0.896	0.720	1.114
PNC (No)							
Yes	0.366	0.107	3.42	0.001	1.442	1.169	1.778
Edu. Hus. (No educ.)							
Primary	-0.275	0.063	-4.38	<0.001	0.760	0.672	0.859
Secondary and higher	-0.270	0.125	-2.17	0.03	0.763	0.598	0.974
Ocp. Moth. (no work)							
Agricultural	-0.015	0.073	-0.2	0.84	0.985	0.854	1.136
Non-agricultural	0.092	0.067	1.38	0.168	1.096	0.962	1.249
Intercept	-1.469	0.191	-7.7	<0.001			

*Reference categories are shown in parentheses

As an indicator of health care service utilization during pregnancy, antenatal care service factors demonstrated a significant association with neonatal mortality. Neonates born from mothers attending 1-3 and four or more antenatal care visits had a 20% and 32% lower risk of mortality than those born from mothers attending no antenatal care visits, respectively. This result is in line with the findings of Singh et al. (2014) in India. Appropriate antenatal care plays a vital 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 infants.

The study revealed an unexpected result on the effect of postnatal care on neonatal death, that is, attending health care services after birth had increased the risk of dying of neonates by 44%. This result is inconsistent with the findings of Baqui et al. (2009). This study also revealed that husbands' level of education and religion are significant predictors of neonatal mortality.

Among the parameter estimates of group membership (i.e., ‘‘not-always-zero’’ versus ‘‘always-zero’’ groups), only access to toilet facility, place of delivery and religion were found to be significant. The results show that women who delivered at health facility were more likely than those who delivered at home to be in the “always-zero” group. The odds for mothers with access to toilet facility to have no NM (being in “always-zero” group) were 61% higher than those having no toilet facility. The results also indicated that the chance for membership in the ‘‘always-zero’’ group (no neonatal death) decreased by a factor of 3.67 for mothers whose religion was protestant holding all other variables constant.

4. Conclusion and Recommendations

4.1 Conclusion

The study has empirically investigated and identified the factors that are associated with the risk of neonatal mortality in Ethiopia based on EDHS 2011 data using methods of count data analysis. Among the count data models considered, the zero-inflated negative binomial model was a better-fit to the data which was characterized by excess zeros and high variability in the non-zero outcome. From the multivariable ZINB regression model, mothers' age at first birth, mothers' highest educational level, number of antenatal visits during pregnancy, husband/partners' educational attainment, postnatal care, place of residence, source of water supply and religion were found to be significant determinants of neonatal mortality in Ethiopia.

4.2 Recommendations

In recent decades, Ethiopia has achieved significant declines in under-five and infant mortality rates. However, neonatal mortality rates have stayed higher than post-neonatal rates. Further interventions are called for to reduce mortality rates among neonates. The findings presented in this study have the following policy implications:

- The survival experience of neonates in rural areas was much lower than those in urban areas. Thus, there is a need to increase access to maternal and child health services in rural areas.
- Improving the level of education of mothers is vital. Education of mothers plays an important role in the survival of neonate, and thus, health programs need to focus on supporting women with little or no education.
- Utilization of antenatal care services should be promoted for the safety of both the mother and the newborn.
- The study revealed that children from households who use unprotected water as a source of drinking were at a higher risk of neonatal death. Thus, efforts should be made to improve access to safe/pipe drinking water.
- Effective programs to reduce early childbearing of women should be implemented so as to decrease neonatal mortality.

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