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IDENTIFICATION OF RISK FACTORS AND REGIONAL DIFFERENTIALS IN UNDER-FIVE MORTALITY IN ETHIOPIA USING MULTILEVEL COUNT MODEL

By

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ACRONYMS

IMR	Infant mortality rate
U5CD	Under five-child death
U5MR	Under-5 mortality rate
TFR	Total fertility rate
UNICEF	United Nations International Children Emergency Fund
OR	Odd ratio
EDHS	Ethiopian Demographic and Health Survey
MDGs	Millennium Development Goals
UNPD	United Nations Population Division
WHO	World Health Organization
USAID	United States Agency for International Development
IGME	UN Inter-Agency Group for Child Mortality Estimation
CSA	Central Statistical Agency

ABSTRACT

Background:

Under-five death (U5CD) is used as a population health indicator. It remains a big issue for developing countries, especially as researchers attempt to distinguish what factors contribute to the high levels. However under five death is still an issue and most studies have not considered regional variations of mothers in their studies.

Objective:

The Objective of this study is to investigate and quantify the regional variation of under-five death per mother and explore the major risk factors of under-five child death taking into consideration various demographic, socio-economic and health and environmental factors.

***Method**:*

Thus, the study analyzes responses mothers on the number of deaths of children aged less than 60 months that they have experienced in their lifetime. Single and multilevel count model are used to explore the major risk factors and regional differentials in under-five mortality in Ethiopia.

Result and conclusion:

Descriptive statistics results show that nationally approximately one third (36%) of mothers have lost at least one under-five child in their lifetime. This figure (percent) is almost similar in all regions except Addis Ababa (which is 16%). The single level Poisson regression (multiple regression) results showed higher incidence rate of under-five deaths for SNNP, Gambela and Ben-Gumuz, while lower rates were estimated for Somalia and Addis Ababa. It was observed that regional differences in under-five mortality were reduced in magnitude when controls were added in the regression model. The relationship between under-five mortality and the explanatory variables age at first birth, mother education level, religion, employment status of mother and economic status of mother are significant. The preliminary plot of estimated/predicted U5CD for all regions versus different predictors shows mortality varies between regions of Ethiopia. The multilevel analysis further showed that there are substantial under-five death variations per mother among regions in Ethiopia, and are significant ($\hat{\boldsymbol{\sigma}}^2_{\boldsymbol{u0}} = 0.14$, se= 0.021 and P-value <0.0001).

Key words: U5CD, Poisson, Extra-Poisson, Negative binomial, Multilevel, MLwiN

CHAPTER ONE
INTRODUCTION

1.1. Back ground of the study

Neonatal mortality refers to the probability of dying within the first month of life; Infant mortality refers to the probability of dying between birth and the first birthday; child mortality rate is the probability of dying between age one and five, and under-five mortality is the probability of dying between birth and the fifth birthday.

Demographers have for a long time been interested in the study of mortality, which is one of the components of population change. Infant and child mortality are among the best indicators of socio-economic development because a society's life expectancy at birth is determined by the survival chances of infants and children.

Child mortality, commonly on the agenda of public health and international development agencies, has received renewed attention as a part of the United Nation's Millennium Development Goals (MDGs). Approximately 9.7 million infants and children under five years of age die each year, with large variations in under-five mortality rates and trends across regions and countries (UNICEF, 2006).

Under-five child mortality is staying higher or even increasing concentrated in few countries despite action plans and interventions made. Mortality rates among children under the age of five remain strikingly high throughout the majority of sub Saharan Africa (UNICEF, 2010). Of the thirty countries with the world's highest child mortality rates, twenty-seven are in sub-Saharan Africa (UNICEF, 1999).The region's under-five mortality in 1998 was 173 per 1000 live births (UNICEF, 2000) compared to the minimum goal of 70/1000 internationally adopted in the 1990 World Summit for Children. According to the UNICEF report (2010), in sub-Saharan Africa 1 in 8 children dies before his/her fifth birthday--nearly 20 times the average for developed regions (1 in 167). Thus, under-five mortality remains a big issue for these developing countries, especially as researchers attempt to distinguish what factors contribute to the high levels.

About 472,000 Ethiopian children die each year before their fifth birthdays (national strategy for child survival in Ethiopia, 2005). This tragic fact places Ethiopia sixth among the countries of the world in terms of the absolute number of child deaths. Of every 100 children in Ethiopia, 14 will not live to celebrate their fifth birthday. The national Under-five Mortality Rate is about 140/1000, with variations among the regions from a low of 114 in the capital city Addis Ababa to a high of 233 in Gambella and 229 in Afar. (Child Health in Ethiopia, 2004).

Disparities in child health between and within countries persisted and widened considerably during the last few decades (Gakidou and King, 2002; Population Reference Bureau, 2004; WHO, 2007; Population Reference Bureau and African Population and Health Research Center, 2008). The reduction of these disparities is a key goal of most developing countries' public health policies, as outlined in the Millennium Development Goal (Black *et al*., 2003; Jones *et al*., 2003; Lee, 2003; WHO, 2005; UNDP, 2007).

It is well recognized that disparities in child health outcomes may arise not only from differences in the characteristics of the families that children are born into but also in the socio-economic attributes of the community where they live (Frankenberg, 1995; Duncan *et al.,* 1998; Robert, 1999; Huie, 2001; Balk *et al.,* 2004; Kravdal, 2004; Angeles *et al.,* 2005; Montgomery and Hewett, 2005). Indeed the incorporation of community-level factors in the analysis of child mortality provides an opportunity to identify the health risks associated with particular social structures and community ecologies, which is a key policy tool for the development of public health interventions (Pickett and Pearl, 2001; Stephenson *et al.,* 2006). Nonetheless, while researchers have devoted considerable attention to the impact of individual-level factors on child mortality, less is known about how community characteristics affect health outcomes for children, even though they have a prominent role in theoretical models (most notably Mosley and Chen, 1984; Schultz, 1984). Existing studies generally have a limited focus in considering regional variation of child mortality.

The main aim of this study is, thus, the determination of risk factors of under-five mortality at the individual and region level; and quantifying their regional variation by using data from the 2005 Ethiopia Demographic and Health Survey.

1.2. Statement of the problem

Many demographers and scholars do believe and recommend the need to conduct in-depth studies on the various aspects of infant and child health status in different demographic, economic and socio-cultural settings. The researcher shares the idea and the main reason behind this research is the need to study the socio-economic, demographic, health and environmental determinants and differentials of infant and child health status in Ethiopia.

Understanding the geographic distribution of under-five mortality is crucial to policy interventions. Mortality in most parts sub-Saharan Africa tends to cluster by area, often identified as high or low-mortality region (WHO, 2005).

Thus, this study tries to address the regional variation of under-five mortality and explore the major risk factors of infant and child death taking into consideration various health, socio-economic and environmental factors such as mother age, mothers' education, place of residence, economic status of the household, etc based on the 2005 Ethiopia Demographic and Health Survey data.

1.3. Objective

General objective: To investigate the existence of regional differentials in under-five mortality as well as the extent to which this variation is related to a set of explanatory variables through single and multilevel count specifications.

Specific objectives

- To identify the most important factors that are related to the death of children under the age of five in Ethiopia.
- To investigate the different levels of the risk factors and evaluate the probability of each risk level.

1.4. Significance of the study

- To give emphases on the factors that have strong association with under-five mortality so that policy directives act on accordingly.
- The international community is committed to MDGs, most of which are closely related to health. In line with this, the results can assist policy makers in the health sector in their effort towards meeting the MDG's related to child mortality.
- The study could be used as a stepping-stone for further studies.

1.5. Limitations of the study

One of the potential limitations of this study is the cross-sectional nature of our analysis. The study uses reported characteristics of mothers and households that may vary within time. Only mother's age at first birth is fixed, others are time-varying covariates. However, in our analysis all covariates were considered fixed during the study period or are constructed based on the state of affairs at the time of the interview.

Generating accurate estimates of under-five mortality poses a considerable challenge because of the limited availability of high-quality data for many developing countries. Vital registration systems are the preferred source of data on child mortality because they collect information as events occur (minimize recall errors from women) and cover the entire population. However, many developing countries like Ethiopia lack vital registration systems that accurately record all births and deaths.

1.6.Organization of the Study

This study is presented in five chapters. The first chapter gives a general background of the study, statement of the problem, objective, its significance and limitation of the study. Chapter 2 deals with the review of related literature on determinants of child death in Ethiopia and the rest of the world, whereas chapter three specifies the data and methodology of the study such as sources of data and variables to be included in the study with their coding and description. Methods of data analysis are also described in this chapter. Chapter 4 reports results from statistical data analysis. Finally, the last chapter presents discussion, conclusion and recommendations based on the findings of the study.

CHAPTER TWO
RELATED LITERATURE REVIEW

Mother's Educational Attainment

Maternal education is a major determinant of child survival, influencing care seeking, morbidity and nutritional status. Only 34% of adult Ethiopian women are literate, compared with 49% of men, and 20% fewer girls than boys enroll for primary school. The U5MR for children whose mothers have no schooling is 121% higher than those whose mothers have at least a secondary education (WHO, 2007).

The relationship between maternal education and child mortality has been the topic of much research. Based on the data obtained from secondary and primary source by interviewing 120 mothers using judgment sampling, Ojikutu (based on chi-square test) asserted that U5MR in Lagos state depends on the educational qualification of mothers. Similarly, the chi square test of independence run by Mahfouz et al. (2009) on Malakal Town – Southern Sudan shows that there is strong association between under five-child mortality and education of mothers.

Belaineh *et al*. (2007) by case control study on Gilgel Gibe Field Research Center, Southwest Ethiopia, found that among the socio-economic factors, maternal education is significantly associated with under-five mortality. By their study, higher under five mortality was observed among mothers whose educational level was elementary and below as compared to mothers who were above elementary school, the odds ratio (OR) being 11.7 (95% CI: 1.5, 91). Other socio-demographic variables did not show statistically significant association with under-five mortality. Maternal education retained its significance after adjusting for other socio-demographic variables. Children who were born to mothers whose educational level is below elementary were 25 times more likely to die compared to children who were born from mothers whose education is above elementary school, OR=24.8 (95% CI: 2.4, 290).

Dashtseren (2002), using logistic regression, found that mother's education is the most significant predictor of infant mortality. He used the 1998 reproductive health survey (RHS) data and vital registration of Mongolia for this analysis.

Maternal education has a substantial impact on infant and child survival through increased awareness of problems and better feeding habits, among other reasons. Caldwell (1991) confirmed that mothers' education is a robust determinant of infant and child survival in Bangladesh. Importantly, Kovsted, Pörtner and Tarp (2002), in a study in Guinea-Bissau, showed that education is only a proxy for actual health knowledge, the real determinant of child health and mortality. Maglad (1993), based on household data from Sudan, revealed that parental education, income per adult and public health programs are significantly and negatively correlated with child mortality; maternal education, in particular, is found to have a larger significant effect than that of the father.

Aguirre (1995) identifies that among health and demographic factors, mothers' education is the most important factor that directly affects child mortality. He used full and partial hazard in the Cox proportional model specification and found that there is a strong association between the instantaneous risk of dying and education in the face of other controls. Net of the other factors considered in the model, infants whose mothers had no education (0 years of schooling) are 13.8 times more likely to die before their second birthday than those whose mothers had attained more than 12 years of schooling (reference group). This relative risk decreases to 4.6 when mothers have primary education and to 2.4 when they have secondary education.

Using data from the first round of Demographic and Health Surveys for 22 developing countries, Desai and Alva (1998) examined the effect of maternal education on three markers of child health: infant mortality, children height-for-age, and immunization status. The logistic regression model, standard errors adjusted for intra cluster correlations, shows a consistent negative relationship between maternal education and the probability of infant death. This model contains variables for maternal education, urban residence and child's age. Children of mothers who attended primary school are less likely to die than are children of mothers with no education. Children of mothers with a secondary-school education are the least likely to experience infant deaths. Among the 22 countries, this effect is statistically significant in 11 countries for primary education and in 15 countries for secondary education. The education variables are jointly significant in 14 countries.

On the same paper, Desai and Alva (1998) examined the effects maternal education by including an expanded set of predictors: access to piped water, access to any type of toilet facilities, whether mother has ever had a partner, whether father/stepfather attended primary school, whether father/stepfather ever attended secondary school. Because mothers' education serves as a proxy for family's socioeconomic situation, introducing direct controls for some of the socioeconomic variables reduces the effect of maternal education. Averaging across the sample countries, the coefficient for primary education changes from -0.181 to -0.145 and for secondary education from -0.703 to -0.520 and the effect of maternal education is statistically significant for 7 and 13 countries for primary and secondary education, respectively. The two education variables are jointly significant in 11 of the 22 countries.

This effect is further reduced by controlling for area of residence through the use of fixed-effects models. Averaging across the sample countries, the coefficient for primary education is -0.153 and for secondary education is -

0.339. A coefficient of -0.153 reflects a 14% reduction in child mortality with only 9 out of the 22 countries showing this level of reduction. Moreover, this effect is statistically significant in only 4 of the 22 countries, even after using a generous one-tailed test. Obtaining secondary education-as opposed to remaining uneducated-has a larger effect, with a mean reduction in the odds of infant mortality of about 27%, but the effect is statistically significant in only 7 of the 22 countries.

Place of residence

Using Demographic and Health Survey (DHS) data, Wang (2002) had investigated determinants of child mortality in low-income countries like Ethiopia both at the national level, and for rural and urban areas separately. DHS data from over 60 low-income countries between 1990 and 1999 reveal that there is significant gap in child mortality between urban and rural areas. Given that the poor are mainly concentrated in rural areas, the above evidence suggests that health interventions implemented in the past decade may not have been as effective as intended in reaching the poor. She uses both ordinary least square (OLS) and weighted least square (WLS) to check the consistency of the estimates.

In a related study, Wang (2003), using the results from the 2000 Ethiopia DHS, examines the environmental determinants of child mortality. She runs three hazard models, the Weibull, the Piece-wise Weibull and the Cox model to examine three age-specific mortality rates: neonatal (under one month), infant (under one year), and under-five mortality by location (urban/rural); and other socio economic and health factors such as female education attainment, religious affiliation, income quintile, and access to basic environmental services (water, sanitation and electricity). The estimation results show that children born in rural areas face much higher mortality risk compared to those born in urban areas. Ethiopia is characterized by severe lack of access to basic environmental resources and strong statistical association is found between child mortality rates and poor environmental conditions.

Differentials by Religion

Based on sample survey of 2015 women (aged 18-50 years) data collected in Chibuto district of Gaza province in southern Mozambique in 2008, Cau *et al.* (2010) studied the effects of religion on child health outcomes through examining the relationship between mother's religious affiliation and child mortality and health. They used religious affiliation a series of dummy variables created as, whether a woman belonged to a Mainline (Catholic or Protestant) church or not, whether she belonged to Zionist church or not, whether she belonged to some other Apostolic or other small churches or not, and whether she didn't belong to any religion. Using the discrete-time logit models, they found that mother affiliation to any denomination significantly decreases the odds of a woman experiencing child death in a given year, compared to women with no religion (p-value<0.05). when they add education to the model (a proxy for socio-economic status), women belonging to Mainline churches (Catholics and Mainline Protestants) and other small Pentecostal-type churches is significantly decreasing the odds of experiencing child death in a given year, net of other factors, relative to not being affiliated with any church (p-value<0.05). However, belonging to Zionist church is not a significant predictor after woman's education is controlled for.

According to the UN (1985) cited in Mengistu (1987), "Moslem women usually experience higher infant and child mortality than Christian women". However, Gaisie (1979) explains that religion per se does not greatly affect infant and child mortality but lower levels of infant and child mortality may be a reflection of the fact that the Christian group may contain more educated mothers than the group consisting of traditional or other worshippers.

Regional variation

Ethiopia is a diverse country and childhood mortality is not evenly distributed throughout the country. Under-5 mortality rates range from a low of 114 in the capital city of Addis Ababa to a high of 233 in Gambella and 229 in Afar, two remote regions. (Child Health in Ethiopia, 2004)

Patel (1980), on the paper he studied about the effects of the health service and environmental factors on infant mortality, found that regional variations in the infant mortality rates of Sri Lanka are large, ranging from 26 per 1000 live births in Jaffna to 91 per 1000 in Nuwara Eliya, a tea estate district. These differences are more strongly associated with regional variations in environmental determinants of mortality than with regional variations in public health expenditure. The most significant environmental factor associated with interregional infant mortality rates was found to be the source of water supply (i.e. tap water, well water or river water). Regional government expenditure on health had only a weak association with infant mortality rates.

Source of water supply

Piped water supply reduces infant mortality directly by reducing the incidence of diarrhea that arises from the ingestion of contaminated water and food, and indirectly when caregivers are able to devote more time to childcare instead of water collection activities (Rabindran *et al.*, 2008).

Patel (1980) found that there was a strong negative relationship between use of well water and regional IMRs in Sri Lanka. High use of well water is associated with low incidence of infant mortality. Well water is the main source of drinking water for 69% of households in Sri Lanka. Multivariate regression analysis yielded a highly significant coefficient of 0.81 and also there was a strong positive association between the extensive usage of river water and the high infant mortality rates of different districts. River water is used directly by 25% of the population of Sri Lanka.

Availability of Toilet facility

A study on West Africa conducted by Togbe *et al*. (1994) showed a high correlation existing between environmental factors (like the quality of water supply, the availability of a toilet and the level of hygiene), the risk of contracting various infectious diseases and infant and child mortality.

Based on the study results of Patel (1980) in Sri Lanka, there was a weak positive association between regional provision of latrines and regional IMRs.

Employment status of mother

By using the proportional hazard model, Esayas (2003) found that working and non working mothers do not differ in terms of mortality of infants but the type of work that a mother is engaged in has a significant effect on infant mortality. According to his study which was based on data from the Ethiopia Demographic and health Survey (EDHS) in year 2000, agriculture/manual work increases infant mortality while professional/technical/clerical reduces infant mortality. The multivariate analyses also support this result.

In contrast to Esayas, Ojikutu (2008) using chi-square test found that occupation of mothers is not a significant contributor to U5MR. Based on data obtained from secondary and primary source by interviewing 120 mothers using judgment sampling, Ojikutu ascerted that U5MR in Legos state does not depend on the occupation of the mothers.

Age at first birth

The age of the mother at the time of the first birth is an important factor for infant and child survival. Mondal *et al.* (2009) using multivariate logistic regression analysis found that the most significant predictors of neonatal, post-neonatal, and child mortality levels are mother's age at birth along with other covariates (immunization, ever breastfeeding, and birth interval).

Infant and child mortality are higher for mothers who are under 20 years of age and lower for children whose mothers aged between 20-29. Neonatal mortality of the children whose mothers aged below 20 years at the time of the child's birth is 9.9 % higher than those children whose mothers are in the age range 20-29 years at the time of giving birth.

Consistent with other studies, Aguirre (1995) stated that maternal age has a U-shaped relationship with child mortality. In effect, both coefficients age and age squared are statistically significant and have the expected direction. That is, the risk of child mortality for children under age two is higher when women are either too young or too old, once parity and other reproductive factors are controlled for.

Economic status of the household

As observed in most studies, household income has significant effect on children survival prospects. Higher mortality rates are experienced in low income households as opposed to their affluent counterparts.

According to Belaineh *et al*. (2007), based on data obtained by using structural questionnaire from Jimma town, Ethiopia, a higher level of wealth score as measured by wealth index has shown a significant reduction in child mortality in a multivariate logistic regression analysis.

CHAPTER THREE
MATERIALS AND METHODOLOGY

3.1. SOURCES OF DATA

The data in this study is based on the 2005 Demographic and Health Survey which is obtained from the Central Statistical Agency (CSA), Ethiopia. The 2005 Ethiopian Demographic and Health Survey (EDHS) is the second compressive survey designed to provide estimates for the health and demographic variables of interest for the following domains: Ethiopia as a whole; urban and rural areas of Ethiopia (each as a separate domain); and 11 geographic areas (9 regions and 2 city administrations). In general, the DHS sample is stratified, clustered and selected in two stages. In the 2005 EDHS a representative sample of approximately 14,500 households from 540 clusters was selected. The sample was selected in two stages. In the first stage, 540 clusters (145 urban and 395 rural) were selected from the list of enumeration areas (EA) from the 1994 Population and Housing Census sample frame. In the second stage, a complete listing of households was carried out in each selected cluster. Between 24 and 32 households from each cluster were then systematically selected, and all women of reproductive age in the households are interviewed.

Thus, this study analyzes responses from each of 9210 women (only those who have ever born a child), out of 14070 women of age 15-49 interviewed in 2005 DHS, on the counts of the number of deaths of children aged less than 60 months that the mother experienced in her lifetime.

3.2. Variables included in the model:

The response variable of this study, Y_{ij}, is a count, which gives the number of deaths of children aged less than 60 months that each mother has experienced in her lifetime. Thus, Y_{ij} takes on values, y_{ij}= 0, 1 … where i denotes the individual mother and j is the region in which the mothers belongs to.

This paper tries to include the most important expected determinants of risk factors of under five-child mortality from various literature reviews and their theoretical justification from the source data. The explanatory variables at individual and household level to be analyzed are grouped as socioeconomic, demographic and health and environmental related factors.

The Socio economic variables under consideration are education level of mother, place of residence, region, economic status of household, employment status of mother, religion. Age of mother at first birth is the demographic variable considered; and source of water supply and availability of toilet facility are considered among health and environmental variables.

Detailed description of socioeconomic, demographic, health and environmental related variables related to maternal death is presented as follows.

No.	Description and Name	Categories
1	Place of residence(RESIDENCE)	(0). Rural (1). Urban
2	Region/Administrative city(REGION)	(1). Tigray (2). Affar (3). Amhara (4). Oromiya (5). Somali (6). Ben-Gumuz (7). SNNP (8). Gambela (9). Harari (10). Dire-dawa (11). Addis Ababa
3	Education level of mother (EDUCMOTH)	(1). no education (2). primary (3). secondary and higher
4	Source of water supply (WATER)	(0). if the household has access to piped water (1). otherwise
5	Employment status of mother (EMPLOMOTH)	(0). Non-working (1). Working
6	Economic status of the household (WEALTH)	(1). Poor (2). Medium (3). Rich
7	Religion (RELIGION)	(1). Christian (2). Muslim (3). Others
8	Availability of toilet facility (TOILET)	(0). if there is a toilet(any kind) (1). otherwise
9	Age at first birth(AGEFIRST)	(0). age < 20 (1). age >=20

3.3. Introduction to Poisson, Extra-Poisson and negative binomial regression analysis

Poisson regression is one of the most popular technique for regression with count data. Here in Poisson model, one of the basic assumptions is that each under five child has the same probability of dying before the age of five. More realistically, these probabilities may vary due to unexplained heterogeneous / unmeasured/ factors like nutritional status of mothers and child, breast feeding, place of delivery, neonatal care, post neonatal care, and the like. Such variation may cause the under five-child death counts to display more variation than predicted by the Poisson model. Extra variation then occurs because of the variability from mother to mother on the probability of their children dying before the age of five (because of the above factors). Assuming a Poisson distribution for a count variable is often too simplistic, because of factors that cause overdispersion.

The Negative Binomial (NB) regression model is a direct extension of the Poisson model that allows for overdispersion. In the Poisson regression model, the dispersion parameter connecting the mean and variance is fixed at one; the NB regression model is simply a Poisson regression that estimates the dispersion parameter, allowing for independent specification of the mean and variance. Because the only difference between the Poisson and the NB lies in their variances, regression coefficients tend to be similar across the two models, but standard errors can be very different. When the outcome variable is overdispersed relative to the Poisson distribution, standard errors from the NB model will be larger but more appropriate. Thus, p-values in Poisson regression are low and confidence intervals are too narrow in the presence of overdispersion.

This study reviewed three modeling strategies for count data and their implementations in SPSS (only for goodness of fit test and descriptive statistics) and MLwiN. Basic Poisson models with and without the consideration of observed heterogeneity is a good starting point for count data modeling. For count data with some evidence of over-dispersion, Negative Binomial regression with a more liberal assumption on variance is able to provide a better solution. If the over-dispersion results from a high frequency of zero counts, advanced composite models such as Hurdle regression, ZIP regression and Latent Class regression might give more satisfactory fit to the data.

However, for the interest of this paper and the nature of the data considered, we only fitted and compared the Poisson, extra-Poisson and negative binomial models along with related statistical tests. Once we explain the Poisson model and its related concepts, other count models are extension of Poisson models and are therefore straightforward.

3.3.1 Poisson regression

3.3.1.1 The multiple regression models

The effect of some factors on a dependent or response variable may be influenced by the presence of other factors through effect modifications (i.e., interactions). Therefore, to provide a more comprehensive analysis, it is very desirable to consider a large number of factors and sort out which are most closely related to the dependent variable. This method, which is multiple Poisson regression analysis, involves a linear combination of the explanatory or independent variables; the variables must be quantitative with particular numerical values for each observation unit. A covariate or independent variable may be dichotomous, polytomous, or continuous; categorical factors will be represented by dummy variables. In many cases, data transformations of continuous measurements (e.g., taking the logarithm) may be desirable so as to satisfy the linearity assumption.

3.3.1.2 Poisson Regression Model with Several Covariates

Let $Y_1, Y_2, \dots, Y_n$ be independent random variables with Y_i denoting the count of the number of U5CD from the i^{th} mother. Let us assume that a discrete random variable Y (number of U5CD) is Poisson- distributed with intensity or rate parameter μ , $\mu > 0$. Then the Poisson probability mass function, with rate parameter μ, is given by:

$$\boldsymbol{p(Y = y) = \frac{e^{-\mu}\mu^{y}}{y!}} \quad y = 0,1,2, \dots \tag{1}$$

where $\boldsymbol{\mu = E[Y]}$, the expected value of $\boldsymbol{Y}$, equals the variance $\boldsymbol{V[Y] = \mu}$. Equality of the mean with the variance is the equidispersion property of the Poisson 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. Let $\boldsymbol{ln(N_i)}$ be an offset, where $\boldsymbol{N_i}$ is defined as the total number of children a mother had in her lifetime (the total number of live births from i^{th} mother).

Our interest focuses on how the mean number of events changes due to changes in one or more of the factors. Suppose that we want to consider K factors, $X_1, X_2, X_3, \dots, X_k$ simultaneously. The expected value of $\boldsymbol{Y_i}$ can be written as:

$$\boldsymbol{E(Y_i) = N_i exp\left(\beta_0 + \sum_{j=1}^{k} \beta_j X_{ji}\right)}$$

Taking natural logarithms, this is equivalent to:

$$\boldsymbol{ln(\mu_i) = \ln(N_i) + \beta_0 + \sum_{j=1}^{k} \beta_j X_{ji}} \tag{2}$$

where $\boldsymbol{\beta}$ is a k+1 dimensional parameter vector affecting under-five mortality levels and $\boldsymbol{exp}\left(\boldsymbol{\beta_0} + \sum_{j=1}^{k} \boldsymbol{\beta_j}\, \boldsymbol{X_{ji}}\right)$ is the risk of the $\boldsymbol{i^{th}}$ mother.

3.3.1.3. Testing Hypotheses in Multiple Poisson Regression

Once we have fit a multiple Poisson regression model and obtained estimates for the various parameters of interest, we want to answer questions about the contributions of various factors to the prediction of the Poisson-distributed response variable. There are three types of such questions:

1. **Overall test taken collectively**: does the entire set of explanatory or independent variables contribute significantly to the prediction of the response variable?
2. **Test for the value of a single factor**: does the addition of one particular variable of interest add significantly to the prediction of response over and above that achieved by other independent variables?
3. **Test for contribution of a group of variables**: does the addition of a group of variables add significantly to the prediction of response over and above that achieved by other independent variables?

Overall Regression Test: We now consider the first question stated above concerning an overall test for a model containing k factors. The null hypothesis for this test may be stated as ″All k independent variables considered together do not explain the variation in the response any more than the size alone.″

In other words,

$$\mathbf{H_0}: \boldsymbol{\beta_1} = \boldsymbol{\beta_2} = \boldsymbol{\beta_3} = \cdots = \boldsymbol{\beta_K} = 0 \tag{3}$$

$$\mathbf{H_1}: \text{Not all } \boldsymbol{\beta_j} = 0 \text{ for } j = 1,2,3, \dots, \mathrm{k}$$

This can be tested using the Deviance (MCMC) test at k degrees of freedom. The deviance statistic (McCullagh and Nelder, 1989) can be thought of as a measure of how well our model fits the data. Generally the deviance is the difference in -2*log (likelihood) values for the fitted model and a saturated model.

The Deviance (log likelihood ratio statistic) is given by:

$$\boldsymbol{D} = 2\left\{\sum \boldsymbol{y_i} \log\left(\frac{y_i}{\widehat{\mu}_i}\right) - \boldsymbol{y_i} + \widehat{\boldsymbol{\mu}}_i\right\} \tag{4}$$

The null hypothesis is rejected if $D > \boldsymbol{X^2}_{\boldsymbol{k},\boldsymbol{\alpha}}$ .Alternatively, if $\boldsymbol{d}$ is the observed value of $\boldsymbol{D}$ and if $P(D > d) = \boldsymbol{p - value} < \alpha$, then $\boldsymbol{H_0}$ is rejected.

Test for contribution of a group of variables:

- **Deviance test**

The contribution of a group of variables to the current model is evaluated by comparing the change in deviance with the chi-square value for the difference in degrees of freedom. Suppose we have two regression models, M0 with p0 parameter(s) and deviance D_0 and M1 with p1 parameters and deviance D_1 where M0 is a sub model of M1. A test of whether the smaller model M0 is adequate to describe the data in comparison to the larger model M1 is based on the Deviance test statistic: $\mathrm{D} = (\mathrm{D}_0 - \mathrm{D}_1)$ which has a Chi-Square distribution with (p1-p0) degrees of freedom. We cannot use Deviance to compare two models when the models are non-nested.

- **Information criteria**

Spiegelhalter et al. (2002) use the deviance with MCMC sampling to derive a diagnostic tool known as the Deviance Information Criterion (DIC), which is a generalization of the Akaike's Information Criterion that includes deviance and the number of parameters estimated in the model.The deviance information criterion (DIC) is given by:

$$DIC = D + pD$$

where D is the posterior mean of the model deviance and pD is the effective number of parameters. The model with the smallest DIC offers the best fit. The DIC can be applied to non-nested models. Note that for single level models the DIC statistic will give the usual deviance (-2 log likelihood) value.

Test for a Single Variable (individual test) Let us assume that we now wish to test whether the addition of one particular independent variable of interest adds significantly to the prediction of the response over and above that achieved by other factors already present in the model. The null hypothesis for this test may be stated as ''Factor X_i does not have any value added to the prediction of the response given that other factors are already included in the model.'' In other words,

$$H_0: \beta_i = 0 \text{ for } i = 1,2,\ldots,k \qquad H_1: \beta_i \neq 0 \tag{5}$$

To test such a null hypothesis, one can use

$$\mathbf{t_i} = \frac{\widehat{\boldsymbol{\beta}}_i}{\mathbf{se}(\widehat{\boldsymbol{\beta}}_i)} \tag{6}$$

where $\widehat{\beta}_i$ is the corresponding estimated regression coefficient and $se(\widehat{\beta}_i)$ is the estimate of the standard error of $\widehat{\beta}_i$. This test statistic has the t-distribution with n-k-1 degree of freedom.

3.3.1.4. Poisson Log linear Models

The Poisson distribution has a positive mean μ. Although a generalized linear model (GLM) can model a positive mean using the identity link, it is more common to model the log of the mean. The log mean is the natural parameter for the Poisson distribution, and the log link is the canonical link for a Poisson GLM. A Poisson log linear GLM assumes a Poisson distribution for Y and uses the log link. The Poisson log linear model with explanatory variable X is (Agresti, 2002)

$$\mathbf{ln\mu_i = \eta_i = X_i\beta} \tag{7}$$

In the general Poisson regression model, we think of μ_i as the expected number of under five-child death from the i^{th} mother and the total number children ever born from the i^{th} mother is N_i. This means parameter μ will depend on the population size and the total number of children ever born from the individual mother. Thus the distribution of Y_i can be written as:

$$\mathbf{Y_i \sim poisson(N_i\mu_i)}$$

where $\mathbf{N_i}$ is the total fertility rate of i^{th} mother and $\mathbf{\mu_i = exp(X_i\beta)}$

The logarithm of the exposure $\log N_i$ is the offset (scale variable) in a generalized linear model terminology. It is differentiated from other coefficients in the regression model by being carried through as a constant and forced to have a coefficient of one (Gelman and Hill, 2007).

Thus, the GLM with an offset is given by

$$\boldsymbol{log\ \mu_i = logN_i + X_i\beta} \tag{8}$$

Including log (exposure) as a predictor in the Poisson regression model in some settings makes sense in that it can allow the data to fit better; in other settings, it is simpler to just keep it as an offset so that the estimated rate μ_i has a more direct interpretation. Furthermore, the number of children born will be equal to the observed deaths if the coefficients of the independent variables, denoted by $\boldsymbol{\beta}$, are all equal to zero. Since $\boldsymbol{N}$ is a constant, any variation in the coefficients of the independent variables will show up affecting the dependent variable and not the number of children born.

3.3.2. Overdispersed (Extra-) Poisson model

It is possible to account for overdispersion with respect to the Poisson model by introducing a dispersion parameter $\boldsymbol{\alpha}$ into the relationship between the variance and the mean:

$$\boldsymbol{Var}(\mathbf{y_i}) = \boldsymbol{\alpha\mu} \tag{9}$$

When $\alpha = 1$ ($or\ near\ to$ 1) we have ordinary Poisson model, when $\alpha > 1$ we have the overdispersed Poisson model. Note that the introduction of the dispersion parameter, however, does not introduce a new probability distribution, but gives a correction term for testing the parameter estimates under Poisson model. The models are fit in the usual way, and the parameter estimates are not affected by the value of $\boldsymbol{\alpha}$, but the estimated covariance matrix is inflated by this factor. This method produces an appropriate inference if overdispersion is modest (Cox, 1983) and it has become the conventional approach in Poisson regression analysis. There are two ways of dealing about overdispersion:

- Adjust estimated standard errors; when we are primarily concerned with testing hypotheses regarding parameter estimates. That is multiplying the standard errors of all the coefficient estimates by the square root of the estimated overdispersion. Without this adjustment, the confidence intervals would be too narrow, and inferences would be overconfident.
- Use an alternative distribution as your random component (i.e., model the extra variability) — When our concern is prediction.

3.4. Test for dispersion

A natural basis for testing the adequacy of the Poisson model is the relationship between $Var(y_i \mid X_i, \beta)$ and $E(y_i \mid X_i, \beta)$. To assess the adequacy of the negative binomial model over the PR model, we test the hypothesis that the mean and the variance are equal (equi-dispersion). Here the diagnostic tests are concerned with checking for this assumption.

Deviance and Pearson Chi-Square divided by the degrees of freedom are used to detect over dispersion or underdispersion in the Poisson regression. Values greater than 1 indicate overdispersion, that is, the true variance is bigger than the mean, where as values smaller than 1 indicate underdispersion, that is, the true variance is smaller than the mean. Evidence of underdispersion or overdispersion indicates inadequate fit of the Poisson model (McCullagh and Nelder, 1989). According to Collett (2003), as a rule of thumb, the Deviance divided by the degree of freedom should be approximately equal to one for a satisfactory model. Similarly, Lindsey (1999) suggests that overdispersion is possible if the deviance is at least twice the degrees of freedom.

We can also test dispersion by specifying extra Poisson variation. Here the variance parameter is estimated, say as $\boldsymbol{\alpha}$, instead of 1, to give the variance as $\boldsymbol{\alpha\mu}$ i.e $Var(y_i|\mu_i) = \alpha\mu_i$ (Rasbash *et al.*, 2003, McCullagh and Nelder, 1989). This α value is used to detect the overdispersion or underdispersion in the Poisson regression. α-value greater than 1 indicate overdispersion whereas α value smaller than 1 indicate underdispersion. Therefore, in testing over dispersion, the hypothesis is given by:

$$\mathbf{H_0}: \alpha = 1 \tag{10}$$

$$\mathbf{H_1}: \alpha > 1$$

It is suggested that the overdispersion parameter $\boldsymbol{\alpha}$ can be estimated by: $\widehat{\boldsymbol{\alpha}} = \frac{\chi^2}{(\boldsymbol{n}-\boldsymbol{k})}$, where $\boldsymbol{\chi^2}$ is the Pearson's chi-square statistic, $\boldsymbol{n}$ is the number of observations, and $\boldsymbol{k}+\mathbf{1}$ is the number of unknown regression parameters in the Poisson model. The Pearson's chi-square statistic is given by:

$$\boldsymbol{\chi^2} = \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} \frac{(y_i-\widehat{\mu}_i)^2}{\widehat{\mu}_i} \quad \text{where} \quad \widehat{\boldsymbol{\mu}}_{\boldsymbol{i}} = \boldsymbol{N_i exp}\left(\boldsymbol{X_i}\widehat{\boldsymbol{\beta}}\right) .$$

This statistic has a χ^2 distribution with 1 degree of freedom. Whenever over dispersion exists in the Poisson regression model (i.e H_0 is rejected), it is recommended to use the standard GPR model i.e. the negative binomial model in place of the PR model.

3.5. Multilevel analysis

3.5.1. Introduction

Multilevel/hierarchical modeling explicitly accounts for the clustering of the units of analysis, individuals nested within groups. Such data structures are viewed as a multistage sample from a hierarchical population. For example, in educational research we may have a sample of pupils (level 1 units) clustered within schools (level 2 units), in demographic and health survey we may have individuals nested within districts and districts nested within regions.

Multilevel analysis is a methodology for the analysis of data with complex patterns of variability, with a focus on nested sources of variability. The best way to the analysis of multilevel data is an approach that represents within group as well as between group relations within a single analysis, where "group" refers to the units at the higher levels of the nesting hierarchy. Very often, it makes sense to use probability models to represent the variability within and between groups, in other words, to conceive the unexplained variation within groups and the unexplained variation between groups as random variability. For example, in a study of women within regions, not only unexplained variation between women but also unexplained variation between regions is regarded as random variable. Such variation can be analyzed through statistical models known as random coefficients models.

The main statistical model of multilevel analysis is the hierarchical generalized linear model, an extension of the generalized linear model that includes nested random coefficients.

3.5.2. The rationale of using multilevel model

- The Probability of child mortality may vary due to factors such as difference in individual philosophy of life, health facility, employment status of mother, access to mass media, religious effect, place of residence, culture, type and quality of food (nutritional status of mothers) before and/or after birth of a child, etc. To test whether these factors show variation between regions, multilevel analysis is the most appropriate.
- Many researchers suggest that individual characteristics and environmental factors vary over space and that this variation has been overlooked when the area or space variations are excluded from the model in the analysis. This means ordinary regression ignores the average variation between regions or area.
- A multilevel Poisson model is effective in capturing the overdispersion in data sets with extra Poisson variation (if any).

3.5.3. Multilevel generalized linear model

The Multilevel generalized model have been described by Wong and Mason (1985), Langford (1990), Mislevy and Bock (1989), and Goldstein (1999). In generalized multilevel models, the multilevel structures appear in the linear regression equation of the generalized linear model.

Now consider the full model equation for the two-level Poisson regression with $\boldsymbol{i^{th}}$ individual mothers are nested within the $\boldsymbol{j^{th}}$ region. Using the logarithmic transformation, the level-1 model with $\boldsymbol{k}$ explanatory variables $\boldsymbol{X_1}, \boldsymbol{X_2}, \dots, \boldsymbol{X_k}$ can be written as:

$$\boldsymbol{ln(\mu_{ij}) = ln(N_{ij}) + \beta_{0j} + \sum_{p=1}^{k} \beta_{pj} X_{pij}} \tag{11}$$

where $\boldsymbol{\beta_{oj}}$ are (random) intercept parameters which are assumed to vary across the regions and $\boldsymbol{\beta_{pj}}$, $\boldsymbol{p = 1, \dots, k}$, are (random) slope parameters which are assumed to vary across the regions associated with the explanatory variables, $\boldsymbol{X_{pij}}$. Note that $\boldsymbol{X_{pij}}$ is the level-1 variable (mother characteristics) differing from one mother to another in the same region, so that it has two suffices. The term $\boldsymbol{ln(N_{ij})}$ is included in the model as an offset. Further, the intercept and the slope coefficients, termed as random coefficients (Goldstein, 1999), can be given by:

$$\boldsymbol{\beta_{pj} = \gamma_p + \mu_{pj}} \ , \quad \boldsymbol{p = 0, 1, 2, \dots, k} \tag{12}$$

and $\boldsymbol{\mu_{pj}}$ is the (random) residuals term at the level- 2 (region level). The residual error $\boldsymbol{\mu_{pj}}$ has a mean of zero and variance specified as $\boldsymbol{\sigma^2_{\mu p}}$.

Now for demonstration let us consider region-specific average number of under-five child death from individual mother, $\boldsymbol{ln(\mu_{ij})}$, on a single level explanatory variable X. Thus, we have two random components (random intercept μ_{oj} and a random slope μ_{1j}) assumed to have a bivariate normal distribution $N_2(0, \Omega_\mu)$, where the variance-covariance matrix is given by:

$$\Omega_\mu = \begin{bmatrix} \sigma^2_{\mu 0} & \sigma_{\mu 10} \\ \sigma_{\mu 01} & \sigma^2_{\mu 1} \end{bmatrix} \tag{13}$$

The model for a single explanatory variable discussed above can be extended by including more variables that have random effects.

Note that, in general, the lowest level residual variance $\boldsymbol{\varepsilon_{ij}}$ is not in the model equation (eq 7), because it is part of the generalized linear model specification.

Note that the number of parameters in a multilevel model is relatively large compared to traditional models. If there are k explanatory variables at the lowest level, the number of estimated parameters in the full model will be $\left(\frac{\boldsymbol{k^2+5k+4}}{\mathbf{2}}\right)$,that is, k+1 fixed parameters, k+1 random variance, and $\frac{k(k+1)}{2}$ random covariance. For example in our study, we have 11 factor levels so the number of estimated parameters in the full model will be 121. This is practically cumbersome. Thus, usually we do not want to estimate the complete model, because this is likely to get us into computational problems, and because it is very difficult to interpret such a complex model. If we add higher-level variable and their interaction with the lowest level, the computational problem and the interpretation will be difficult. Fortunately, we do not have to estimate the complete model. We need to limit ourselves to parameters that have proven their worth in previous research, or are interesting in view of our theoretical problem.

If we have no strong theories, we can use an exploratory procedure to select a model. An attractive procedure is to start with the simplest possible model, the intercept-only model, and to include the various types of parameters step-by-step. After all, we will identify which independent variables have random slopes, which have fixed and at each step, we inspect the results to see which parameters are significant.

3.5.3.1. Random intercept-only model

Let us first present the random intercept-only model. It is the simple case of a general multilevel model. Since Poisson does not consider the error at the individual level, we have:

$$\boldsymbol{ln(\mu_{ij}) = ln(N_{ij}) + \beta_{0j}} \tag{14}$$

The coefficient $\boldsymbol{\beta_{0j}}$ is called the level-2 (region) random coefficient, which in this model is a random intercept. This random intercept is modeled further as

$$\boldsymbol{\beta_{0j} = \gamma_0 + \mu_{0j}} \tag{15}$$

where $\boldsymbol{\gamma_0}$ is a fixed coefficient and $\boldsymbol{\mu_{0j}}$ is a random term that is independently normally distributed with mean 0 and variance $\boldsymbol{\sigma^2_{\mu 0}}$ (random intercept variance). Substituting equation (15) into equation (14) yields the model:

$$\boldsymbol{ln(\mu_{ij}) = ln(N_{ij}) + \gamma_0 + \mu_{0j}} \tag{16}$$

This model is also named as empty Poisson regression model (null model). A null model contains only a response variable, and no explanatory variables other than an intercept. Thus, $\boldsymbol{\sigma^2_{\mu 0}}$ measures regional variations of under five-child death i.e. it provides an initial estimate for the intra-class correlation in the response variable ''number of U5CD per mother''.

3.5.3.2. The random intercept model

Here we analyze a model with all lower level explanatory variables fixed. This means that the corresponding variance components of the slopes are fixed at zero, $\boldsymbol{i.e}, \boldsymbol{\beta_{pj} = \gamma_p}$ $since$ $\boldsymbol{\mu_{pj} = 0}$ $for\ all\ p = 1,2, \dots, k$

Only the intercept parameter is allowed to vary across the regions, that is,

$$\boldsymbol{\beta_{0j} = \gamma_0 + \mu_{0j}} \tag{17}$$

As a result, the full random intercept model is given by:

$$\boldsymbol{ln(\mu_{ij}) = ln(N_{ij}) + \gamma_0 + \sum_{p=1}^{k} \gamma_p X_{pij} + \mu_{0j}} \tag{18}$$

The only random part in this model is $\boldsymbol{\mu_{0j}}$, which has a mean of zero and variance $\boldsymbol{\sigma^2_{\mu 0}}$. In this model, we assess the contribution of each individual explanatory variable. We can test the improvement of the final model chosen in this step by computing the difference of the deviance of this model and the previous model (the intercept-only model).

3.5.3.3. The random coefficients model

It is conceivable that the relationship between an explanatory variable and the response is not the same across all regions. For example, the effect of mother education level may not have equal influence on under five-child death of each region. If we fit a model based on the same predictors on the response variable for all regions separately, we may obtain different intercept and slopes for each region.

Thus in this model we will assess whether any of the explanatory variables has a significant variance component between level 2 (regions). This model allows both the intercept and the slope parameters to vary across regions. The model considered is:

$$ln(\mu_{ij}) = \boldsymbol{ln(N_{ij}) + \gamma_0 + \sum_{p=1}^{k} \gamma_p X_{pij} + \sum_{p=1}^{k} \mu_{pj} X_{pij} + \mu_{0j}} \tag{19}$$

In this model, the first part of the right hand side, $\boldsymbol{ln(N_{ij}) + \gamma_0 + \sum_{p=1}^{k} \gamma_p X_{pij}}$, is called the fixed part of the model because the coefficients are fixed. The remaining part, $\boldsymbol{\sum_{p=1}^{k} \mu_{pj} X_{pij} + \mu_{0j}}$, is called the random part. Testing random slope variation is best done on a one-by-one basis. Variables that were omitted in the model eq (18) may be analyzed again at this step: it is quite possible for an explanatory variable to have no significant mean regression slope (as tested in eq (18)) but to have a significant variance component for this slope. After deciding which slopes have a significant variance between level 2 (regions), we can add all the variance components in a final model and use the chi-square test based on the deviances to test whether the final model of eq(19) fits better than the final model of eq(18). Note that model of eq (19) includes additional parameters, the covariance between the slopes (Hox, 1995).

3.5.4. The multilevel Poisson model

As it was mentioned previously, the negative binomial multilevel model is derived as an extension of the Poisson. So first, let us define the Poisson multilevel model.

Let $\boldsymbol{\mu_{ij}}$ be the expected number of under-five child death. The log link function for the Poisson model with random coefficients is:

$$\boldsymbol{ln(\mu_{ij}) = \eta_{ij} = X_{ij}\beta + \sum_{p=0}^{k} \mu_{pj} X_{pij}} \tag{20}$$

If we include the offset, the model will be written as:

$$\boldsymbol{ln(\mu_{ij}) = ln(N_{ij}) + X_{ij}\beta + \sum_{p=0}^{k} \mu_{pj} X_{pij}} \tag{21}$$

where $\boldsymbol{N_{ij}}$ is the total fertility rate of $\boldsymbol{i}^{th}$ mother in $\boldsymbol{j}^{th}$ region, $p = 0,1,2, \dots, k$ with $\boldsymbol{k}$ being the total number of random coefficients in the model including the intercept. Here the coefficients are random at level two (region). The (level-1) individual randomness solely defines the probability distribution of the observed response (Rasbash *et al.*, 2009). $\mathbf{X_{pij}}$, $\mathrm{p} = 0,1,2, \dots, \mathrm{k}$ is a level-1 variable for the $\boldsymbol{i^{th}}$ mother in the $\boldsymbol{j^{th}}$ region including the intercept, and $\boldsymbol{X_{oij} = 1}$. It is assumed that the vector $(\boldsymbol{\mu_{0j}, \mu_{1j}, \dots, \mu_{pj}})$ is independently distributed with means zero and has a multivariate normal distribution with a symmetric variance-covariance matrix. The variances and covariances of the level-two random effects are denoted by:

$$\boldsymbol{var(\mu_{pj}) = \sigma^2_{\mu p} \quad p = 0, 1, 2, \dots, k} \tag{22}$$

$$\boldsymbol{cov(\mu_{pj}, \mu_{sj}) = \sigma_{\mu ps} \quad p = 0, 1, 2, \dots, k \qquad and \quad p \neq s}$$

The probability distribution of Y_{ij} is Poisson distribution so that the probability that Y_{ij} takes the specific value y_{ij} is:

$$p(Y_{ij} = y_{ij}) = \frac{exp^{\mu_{ij}} \mu_{ij}{}^{y_{ij}}}{y_{ij}!} \qquad y_{ij} = 0,1,\ldots \tag{23}$$

with the usual property that $E(Y_{ij}) = var(Y_{ij}) = \mu_{ij}$ which equals to $\exp(\boldsymbol{\eta_{ij}})$ from equation (20).

For any given region, the exponential of each element which is related to an individual covariate, $\boldsymbol{exp(\beta_p)}$, of the fixed effects vector $\boldsymbol{\beta}$ gives the multiplicative effect on the mean number of events $\boldsymbol{\mu_{ij}}$ for a unit increase in the corresponding covariate, $\boldsymbol{X_{pij}}$ assuming that all the other covariates are held constant. In the case of qualitative predictors, it gives the multiplicative effect of being in the specified category compared to the base.

The level 2 random component, Ω_μ, measures the variation of $\boldsymbol{\mu_{ij}}$ between level 2 units, here regions. The first element in Ω_μ, $\mathrm{var}(\boldsymbol{\mu_{0j}})$, gives the dispersion related to the intercept of the model between regions. If the model includes qualitative covariates, the intercept represents the joint effect of all their reference categories. In other words $\mathrm{Var}(\boldsymbol{\mu_{0j}})$ gives between regions unexplained heterogeneity of mean number of under five-child death.

The interpretation of the elements in the remainder of Ω_μ depends on the level at which the corresponding covariate is measured. For covariates defined at level-1, $\boldsymbol{X_{pij}}$, $\boldsymbol{Var(\mu_{pj})}$ gives the random variation of the corresponding effect ('slope'), $\boldsymbol{\beta_p}$, between regions. Further, the covariance between the random intercept and the random slope, $\boldsymbol{Cov(\mu_{0j}, \mu_{pj})}$, is used to calculate the correlation between the intercept and the corresponding 'slope' (Goldstein, 1999), that is,

$$cov(\beta_{0j}, \beta_{pj}) = cov(\gamma_0 + \mu_{0j}, \gamma_p + \mu_{pj}) = \delta_{\mu op} \quad (24)$$

For the interpretation of this covariance, the sign is probably the most important. Negative sign indicates an inverse relation between the random intercept and the corresponding random slope. On the other hand, a positive sign of the covariance between the random intercept and a random slope indicates that the group/region with a relatively high intercept also has a relatively high slope.

3.5.5. The multilevel negative binomial model

The multilevel negative binomial model is derived by allowing for between individuals random variation of the expected number of events $\boldsymbol{\mu_{ij}}$ in Eq. (20). In the negative binomial model, the mean $\boldsymbol{\mu_{ij}}$ is replaced with the random variable $\boldsymbol{\mu^*_{ij}}$:

$$ln\, \mu^*_{ij} = \eta^*_{ij} + \varepsilon_{ij} \quad (25)$$

where $cov(\varepsilon_{ij}, \mu^*_{ij}) = \mathbf{0}$ *and* $exp(\varepsilon_{ij})$ follows a gamma probability distribution, $\Gamma(v)$ with mean 1 and variance $\alpha = v^{-1}$. Integrating with respect to ε_{ij} (Cameron and Trivedi, 1986) the resulting probability distribution is

$$p(Y_{ij} = y_{ij}) = \frac{exp[-exp(\eta^*_{ij}+\varepsilon_{ij})]exp[\eta^*_{ij}+\varepsilon_{ij}]^{y_{ij}}}{y_{ij}!} \quad (26)$$

One version of the multilevel negative binomial model is obtained as:

$$p(Y_{ij} = y_{ij}) = \frac{\Gamma(y_{ij}+v)}{\Gamma(y_{ij}+1)\Gamma(v)} \frac{v^v \mu_{ij}{}^{*y_{ij}}}{(v+\mu^*_{ij})^{v+y_{ij}}}, \quad y_{ij} = 0,1,\ldots \quad (27)$$

where $\boldsymbol{E(Y_{ij} = y_{ij}) = \mu_{ij}^* = exp(\eta_{ij}^*)}$. This is similar to the multilevel Poisson model, but the variance, $\boldsymbol{var(y_{ij}) = \mu_{ij}^* + \alpha\mu_{ij}^{*2}}$, is larger than the variance of multilevel Poisson model, where $\boldsymbol{\alpha}$ is the dispersion parameter.

3.5.6. The single level negative binomial model

Cameron and Trivedi (1986) give a detailed discussion of the single level negative binomial regression model. This specification ignores possible clustering of level one units within level-2 ones and, therefore, any random variation between level 2 units, $\boldsymbol{\mu_j^*}$, in Eq.(25) cannot be accommodated in the model.

There are many variants of negative binomial model, the most common one is Negbin2 model proposed by Cameron and Trivedi (1966) with probability function:

$$\boldsymbol{p(Y_i = y_i) = \frac{\Gamma(y_i+v)}{\Gamma(y_i+1)\Gamma(v)} \frac{v^v {\mu_i}^{*y_i}}{(v+\mu_i^*)^{v+y_i}}} \tag{28}$$

where $\boldsymbol{\mu_i^*}$ is the mean of $\boldsymbol{Y_i}$ and $\boldsymbol{v}$ is the inverse dispersion parameter, which is defined as:

$$\boldsymbol{ln\mu_i^* = X_i\beta + \varepsilon_i} \tag{29}$$

where $\boldsymbol{\mu_i^* = E(Y_i) = exp(X_i\beta),\ and\ \ var(Y_i) = \mu_i^* + \alpha\mu_i^{*2}}$. All other elements are defined as before.

Note that a Poisson random variable is a special case of a negative binomial random variable when $\boldsymbol{v}$ is allowed to become infinite. This is further evidence of the flexibility of the negative binomial distribution since there are infinitely many other choices for $\boldsymbol{v}$ that yield something other than a Poisson distribution.

3.6. Estimation techniques

The statistical theory behind the multilevel generalized linear model is complex. The model parameters to be estimated in most generalized multilevel linear models are the fixed regression coefficients and the covariance matrix of the random effects (the variance for a random-intercept model). The most commonly used estimation methods are maximum likelihood (ML), Marginal quasi-likelihood (MQL), penalized quasi-likelihood (PQL) and Markov chain Monte Carlo (MCMC).

One problem in these model concerns the estimation of residuals at higher levels of the model, since these are non-linear with respect to the responses. This is solved by using a Taylor series approximation (first- or second-order) to estimate the level- 2 residuals.

ML estimation is not straightforward for generalized multilevel linear models since the likelihood involves integrals that cannot be solved analytically. MQL and PQL are the two prevailing approximation procedures. Both MQL and PQL rely on the Taylor expansion to achieve the approximation. They can be fitted using iterated generalized least square (IGLS) or restricted iterated generalized least square (RIGLS). Simulations have shown that MQL tends to overestimate the higher-level variance parameters. Second-order PQL estimation is the most accurate approximation, but problems of convergence are more likely to incur particularly if there are one or more large residuals estimated in the model. Technical details can be found, e.g., in Breslow & Clayton (1993), Goldstein (1991), Rodriguez & Goldman (1995), or Goldstein and Rasbash (1996).

Markov chain Monte Carlo (MCMC), which is a more computer-intensive method that requires large iterative simulations, can be used to approximate the integration over the random effects distribution (Brown, 2009).

In this study, the estimation for both single level and multilevel count models are carried out using Metropolis-Hasting (MH) MCMC sampling method.

CHAPTER FOUR
STATISTICAL DATA ANALYSIS

4.1 Descriptive statistics

Before any advance statistical analysis, it is better to examine the overall picture of the data. The distribution of the number of under-five mortality per mother and the cross tabulation of region by explanatory variables will be our subsequent task in this section.

Table 4.1. Number of mothers that experienced U5CDs.

Number of U5CD	Number of mothers	Percent	Cumulative Percent
0	5897	64.0	64.0
1	1881	20.4	84.5
2	793	8.6	93.1
3	379	4.1	97.2
4+	260	2.8	100.0
Total	9210	100.0	
Mean	0.61		
Variance	0.995		
Skewness	2.160		
Kurtosis	5.436		

Table 4.1 shows descriptive statistics of the number and percentage of U5CD that the mothers in the sample have encountered in their lifetime. It can be seen that 64% of the mothers have not faced any U5CD in their lifetime, where as 2.8% of the them faced 4 or more U5CD. If we observe the overall pattern of U5CD at the national level, it is highly skewed to the right with excess zeroes.

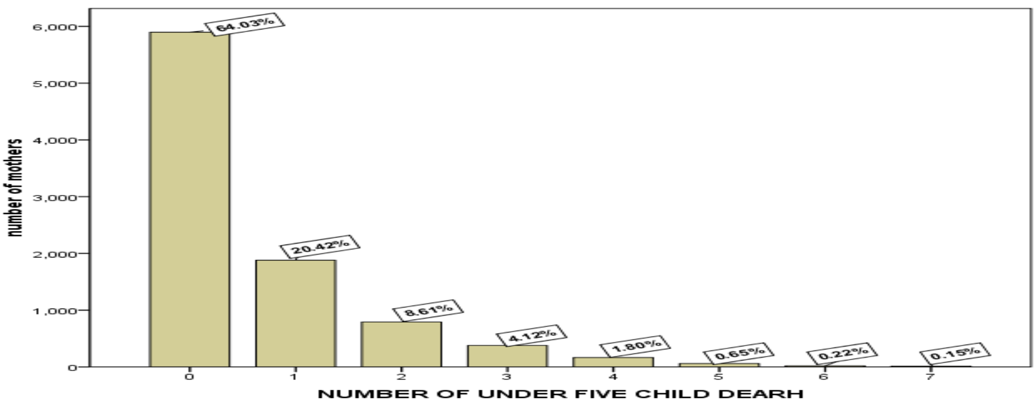

Figure 1: A bar graph of the number of U5CD per mother.

Table 4.2 presents summary statistics of the variables that are assumed to affect the U5CD and its regional distribution. The variables included mothers' education level, place of residence, region, economic status, employment status, religion, age at first birth, source of water supply and availability of toilet facility.

Table 4.2: Regional differentials in under-five mortality by selected background variables (in percentage).

category/variable		Region												
		Tigray	Afar	Amhara	Oromiya	Somali	Ben-gumz	SNNP	Gambela	Harari	Addis ababa	Dire dawa	**Total**	**U5CD >=1**
Mother educ-level	no education	81.64	92.59	86.2	77.2	95.44	81	76.32	66.49	55.4	24.28	55.44	**74.05**	**85.66**
	primary	11.4	3.79	9.84	17.24	2.28	15.54	19.04	26.31	16.09	24.28	17.91	**15.08**	**11.32**
	secondary +	6.96	3.62	3.89	5.55	2.28	3.45	4.64	7.21	28.51	51.44	26.65	**10.87**	**3.018**
Type of place of residence	urban	11.4	12.07	8.49	10.12	16.16	10.05	9.34	16.22	49.9	95.2	67.38	**22.48**	**13.19**
	rural	88.6	87.93	91.5	89.88	83.84	89.95	90.66	83.78	50.1	4.8	32.62	**77.52**	**86.81**
Toilet facility	toilet facility	18.36	9.14	31	25.15	17.11	45.53	67.12	28.65	49.29	93.14	65.03	**40.64**	**35.5**
	no facility	81.64	90.86	69	74.85	82.89	54.47	32.88	71.35	50.71	6.86	34.97	**59.36**	**64.5**
Age at 1st birth	'age'< 20	76.97	67.24	81.8	75.24	66.54	84.62	73.25	82.52	70.47	61.87	72.28	**74.73**	**81.32**
	'age'>=20	23.03	32.76	18.1	24.76	33.46	15.38	26.75	17.48	29.53	38.13	27.72	**25.27**	**18.68**
Source of water	piped water	23.95	15.00	19.6	19.92	12.17	17.9	18.76	27.57	51.12	96.02	82.52	**30.52**	**23.03**
	otherwise	76.05	85.00	80.4	80.08	87.83	82.1	81.24	72.43	48.88	3.98	17.48	**69.48**	**76.97**
Economic status of the household	poor	58.61	78.97	38.7	42.85	80.23	40.5	29.1	53.51	13.03	0.82	19.83	**40.43**	**44.16**
	middle	18.81	5.86	22.4	19.92	5.32	24.18	24.18	8.11	10.18	0.55	5.76	**15.94**	**18.65**
	rich	22.58	15.17	38.7	37.23	14.45	35.32	46.72	38.38	76.78	98.63	74.41	**43.63**	**37.19**
Employment status of mother	working	47.55	8.79	35.3	37.23	10.08	43.96	27.75	33.15	39.92	52.95	37.74	**34.77**	**35.38**
	not working	52.45	91.21	64.6	62.77	89.92	56.04	72.25	66.85	60.08	47.05	62.26	**65.23**	**64.62**
Religion	orthodox	97.49	7.41	83.5	31.87	2.09	33.28	23.75	23.78	29.53	80.93	38.81	**45.3**	**42.32**
	Muslim	2.51	91.03	16.0	48.6	97.34	45.84	13.55	7.93	68.02	9.88	58.21	**35.16**	**37.19**
	others	0.00	1.55	0.35	19.53	0.57	20.88	62.7	68.29	2.44	9.19	2.99	**19.54**	**20.50**
U5CD	**no u5cd**	**62.71**	**67.41**	**58.8**	**60.81**	**73.00**	**58.56**	**56.13**	**66.67**	**72.51**	**84.36**	**65.67**	**64.03**	**-**
	u5cd >=1	**37.29**	**32.59**	**41.1**	**39.19**	**27.00**	**41.44**	**43.87**	**33.33**	**27.49**	**15.64**	**34.33**	**35.97**	**-**

Overall, less than one-fourth (22.48%) of the respondents (mothers) live in urban areas while more than three fourth (77.5%) of them live in rural areas. The regional variation of mothers' place of residence for rural ranges from 4.8% of Addis Ababa to 91.5 Amhara. From a theoretical perspective, place of residence is an important determinant of child survival. Mothers living in urban areas have a higher chance of getting health service (easily accessed) and are aware of the benefit of medication than mothers who reside in rural areas. Table 4.2 reveals that about 86.8% of women living in rural areas have lost at least one child in their lifetime. This is in sharp contrast to the figure in urban areas (which is 13.2%).

According to various literatures, maternal education level strongly affects child health. Table 4.2 reveals that 85.7% of mothers who have no education have lost at least one child in their lifetime, while for mothers with secondary and higher education this figure is just 3%. Concerning regional level of education attainment, Addis Ababa as well as Harari and Dire dawa administrative city had the highest proportion of women with secondary and higher education while the other regions account for only less than 7.3% of this category. The worst educational indicators are observed in Somalia and Afar regions. At the national level, only 10.87% of women had secondary and higher education and the proportion of women who had no education constitute 74.05 percent.

Results in Table 4.2 also show the sanitation indicators, source of water and type of toilet facility. Better sanitation was most lacking in Afar, Somali and Tigray regions of Ethiopia: more than 90 percent of women from Afar region had no toilet facility. Piped water supply reduces infant mortality directly by reducing the incidence of diarrhea that arises from the ingestion of contaminated water and food, and indirectly when caregivers are able to devote more time to childcare instead of water collection activities.

Another maternal variable that has a strong bearing on the survival prospects of a child is the mother's age at the time of first birth. In all regions, the minimum percentage of women that give the first birth before they reach 20 years is 60 percent. If we see the regional variation, 85% of the women from Ben-gumuz gave the first birth before they reach age 20 and are followed by Gambela (82.52%) and Amhara (81.81%).

Table 4.2 also reflects that nationally approximately one third (36%) of mothers have lost at least one under-five child in their lifetime.

4.2 Single level analysis

4.2.1 Determinants of U5CD: Model identification

The multiple Poisson regression analysis with and without the over-dispersion parameter were used to identify the basic determinants of the risk factors of under five-child death at national level. The fitted dispersion parameter (α) for Poisson model is tested to check whether it is significant or not. If so, the negative binomial model is the immediate solution to accommodate this over-dispersion. Thus, under this topic three different count models are fitted: Poisson, over dispersed Poisson and negative binomial model.

4.2.2 Goodness-of-fit and Test for dispersion

Turning first to the main effects model or model selection, Table 4.3 shows the results of the Poisson and negative binomial regression fit statistics.

Table 4.3 Test for Goodness of fit between Poisson and Negative Binomial Regression Models.

Criteria	Estimate	Poisson model	Negative binomial model
Deviance	value	9149.765	5898.824
	df	9188	9188
	Value/df=$\hat{\sigma}^2$	0.996	0.642
Pearson chi-square	value	9463.299	6176.079
	df	9188	9188
	Value/df=$\hat{\sigma}^2$	1.03	0.672
Log-likelihood	value	-8497.847	-8600.949

For the Poisson model, the Pearson Chi-square and deviance values divided by the degrees of freedom are sufficiently close to 1. But for the negative binomial model, both the Pearson Chi-square and deviance ratios are far from 1. This is a possible indication that the fit of the Poisson model is adequate, whereas that of the negative binomial model is not. However, we have to apply a formal statistical test of dispersion. Given $Var(y_i) = \alpha\mu_i$, we test $\mathbf{H_0}: \alpha = 1$ versus $\mathbf{H_1}: \alpha > 1$. The chi-square test statistic is $\boldsymbol{\chi^2_{cal}} = 3.301$ with P-value of 0.0692. Thus, we do not reject $\mathbf{H_0}$ and conclude that there is no evidence that our response is not Poisson distributed and no gain in model fit by allowing for overdispersion. Thus in the analyses discussed below, the Poisson specification is used.

4.2.3. RESULTS OF POISSON REGRESSION ANALYSIS

We now fit a Poisson regression model to analyze the risk factors and regional variation in child mortality. To discern how the different variables of interest operate to affect mortality, the variables are introduced into the regression in stages. The first model (model I) only includes dummy variables for the region the mother was living in at the time of the survey. This establishes regional differentiation of mortality. Model II extends model I through the addition of socioeconomic controls including maternal education level, place of residence, mother religion, economic status and mother employment status. Model III updates Model I with the inclusion of health and environment variables and the final model (model IV) adds all variables under study in an attempt to differentiate the most significant factors of U5CD. The results are given in Table 4.4.

It is reasonable to assess the magnitude of the effect of several factors acting jointly over and above their effects considered separately. In other words, the extent to which the effect of one factor changes for different values of one or more other factors (interactions effect) needs to be measured. The significance of the interaction effects were looked at by adding them into the main effects model one at a time. According to our results, all three-way and higher-level interaction effects were found to be insignificant. From the two-way interactions, regions are interacting with place of residence, education level, work status and religion. In addition, source of water supply and employment status of mother, source of water supply and religion, and employment status of mother and religion were significant. This may call us to use a multilevel model. However, the inclusion of these terms introduces complexity to the analysis and interpretation of results. Therefore, no interactions are included in the analysis.

Goodness of fit test for the fitted multiple Poisson regression models (models I-IV) was assessed using the deviance (MCMC). Accordingly, all the models adequately fit the data at 0.05 level of significance ($p<0.0001$). In other words, at least one $\boldsymbol{\beta}$ is significantly different from zero in all models. In addition, significance was determined using deviance upon explanatory variable inclusion.

The deviance test of mode I against the model II (χ^2 =17281.94 -17034.92= 247.02 with p-value<0.0001) shows that the addition of socio-economic variables has significantly improved the fit of the model. The same can also be said about model III in comparison to model I (though the reduction in the deviance is lower). Furthermore, Model IV provides a significantly improved fit as compared to model II ($\chi^2 = 17.41$ with p-value=0.0006). Thus, we can conclude that model IV is the best fit, and our subsequent discussion focuses on this model.

The results suggest significant regional variations in child mortality in Ethiopia. Model IV shows that the risk of child mortality was 1.53 times higher among children born to mothers in SNNP region as compared to children born in Addis Ababa. Model IV further suggests that the risk of child mortality in Amhara region was 32.2% higher than the risk in Addis Ababa. Somali region is found to have the lower risk of under five-child mortality per mother and was 24 percent lower than Addis Ababa. This might be due to some bias in the representativeness of the regional estimates for the Somali, primarily because the sample excluded the nomadic population. In the Somali Region, only three of the nine zones (Jijiga, Shinile and Liben) were covered.

Model IV also suggest that the risk of under five-child mortality was approximately 1.5 times higher among children born to mothers in SNNP and Gambela regions as compared to Addis Ababa.

Results in Table 4.4 also provide estimates of the effect of some selected individual- and household-level characteristics of mothers on the mortality of their children. Result in Model IV show that children of mothers with no education have approximately 2.5 times higher risk of mortality compared to children whose mothers had a secondary and higher education. Compared with children whose mothers have secondary and higher education, children with mothers who have primary education were about 1.9 times more likely to die before reaching five years of age. Generally, educational level of mothers is an important and significant factor of under-five child mortality risks in Ethiopia.

Results in Table 4.4 (model IV) indicate that children born from mothers whose age at first birth is greater than 20 have significantly lower mortality compared to those born from mothers whose age at first birth is less than or equal to 20.

Though place of residence, source of water supply and availability toilet facility are expected to be important characteristics for under-five child mortality, they are found to have no significant effect on under-five child mortality in this analysis.

Economic status, employment status of mothers and religion of mothers are among the socio economic factors that are included in this study. Table 4.4 of model IV shows that under-five mortality risk experienced by children of working mothers is 13% higher than children of non-working mothers. It was also found that under-five child mortality risk is 10% lower for children of poor mothers compared to children of rich mothers. This is quite unexpected, and might be due to poor data quality pertaining to classification of households' economic status as poor, medium and rich (note, for example, that 98.63% of the households in Addis Ababa are classified as rich (Table 4.2)). Finally, religion of mothers remains a significant predictor of under-five child mortality. Children of orthodox mothers and others (protestant, traditional, etc) have a significantly lower mortality risk compared to those of Muslim mothers.

Table 4.4. Poisson model for under-five mortality by region of residence and for selected independent variables, 2005, EDHS.

Variables/predictors	Models											
	I			II			III			IV		
	β	$SE(\beta)$	$Exp(\beta)$	β	$SE(\beta)$	$Exp(\beta)$	β	$SE(\beta)$	$Exp(\beta)$	β	$SE(\beta)$	$Exp(\beta)$
Intercept	*-2.548**	*0.075*	0.078	-2.884*	0.128	0.056	-2.308*	0.086	0.099	*-2.963**	*0.133*	0.052
Region (Addis Ababa)			1			1			1			1
Tigray	*0.601**	*0.081*	1.824	0.139	0.1	1.149	0.405*	0.094	1.499	*0.132*	*0.1*	1.141
Affar	*0.572**	*0.092*	1.772	0.222	0.107	1.249	0.351*	0.1	1.42	*0.007*	*0.107*	1.007
Amhara	*0.734**	*0.081*	2.083	0.29*	0.095	1.336	0.555*	0.089	1.742	*0.279**	*0.095*	1.322
romiya	*0.582**	*0.081*	1.789	0.125	0.094	1.133	0.394*	0.089	1.483	*0.118*	*0.095*	1.125
Somali	*0.280**	*0.097*	1.323	-0.286*	0.11	0.751	0.079	0.105	1.082	*-0.277**	*0.111*	0.758
Ben-Gumuz	*0.844**	*0.081*	2.326	0.36*	0.1	1.433	0.688*	0.094	1.99	*0.354**	*0.1*	1.425
SNNP	*0.745**	*0.083*	2.106	0.402*	0.096	1.495	0.627*	0.087	1.872	*0.424**	*0.097*	1.528
Gambela	*0.698**	*0.096*	2.009	0.378*	0.106	1.459	0.53*	0.1	1.699	*0.367**	*0.106*	1.443
Harari	*0.582**	*0.098*	1.789	0.222*	0.107	1.249	0.445*	0.102	1.56	*0.207**	*0.108*	1.23
Dire-dawa	*0.601**	*0.098*	1.824	0.242*	0.104	1.274	0.532*	0.1	1.702	*0.232**	*0.105*	1.261
Residence (Rural)						1						1
Urban				-0.049	0.056	0.952				*-0.033*	*0.06*	0.968
Education level(secondary and higher)						1						1
No education				0.93*	0.097	2.535				*0.904**	*0.097*	2.469
primary				0.649*	0.102	1.914				*0.622**	*0.102*	1.863
Employment status of mother (Non-working)						1						1
Working				0.122*	0.028	1.13				*0.122**	*0.028*	1.13
Economic status (Rich)						1						1
Poor				-0.117*	0.035	0.89				*-0.1**	*0.039*	0.905
Medium				-0.032	0.037	0.969				*-0.022*	*0.038*	0.978
Religion (Muslim)						1						1
Orthodox				-0.123*	0.039	0.884				*-0.13**	*0.039*	0.878
Others				-0.215*	0.046	0.807				*-0.221**	*0.047*	0.802
Source of water supply (otherwise)									1			1
Access to piped water							-0.104*	0.037	1.038	*0.011*	*0.04*	1.011
Toilet facility (otherwise)									1			
if there is a toilet(any kind)							-0.157*	0.032	1.033	*-0.057*	*0.037*	0.945
Age at first birth(age >=20)												1
age < 20										*0.142**	*0.035*	1.153
Deviance	*17281.940**			*17034.920**			*17241.480**			*17017.510**		
DIC:	17292.89			17052.66			17254.69			17039.20		
Degree of freedom	11			19			13			22		

Reference categories are in parentheses. *Significant (P-value <0.05)

4.3. MULTILEVEL ANALYSIS

4.3.1. Preliminary data analysis

This is basically with the expectation that there would be a difference in the number of under-five child mortality from individual mothers among the regions. The preliminary analysis using Poisson regression in the previous section also revealed such differences. We did this considering the regional variation of mothers' place of living as one factor of under-five child mortality.

Before applying a formal multilevel model, the hierarchies of the data were analyzed by exploratory data analysis graphically. Let us now set up a model with a separate term for each region. We will also allow a separate place of residence (urban and rural) slopes for each region. This is with the objective of checking whether difference in mothers' place of residence has an effect on U5CD of each region.

Figure 2 shows the plot of the predicted value of U5CD for all regions versus the selected predictor, place of residence. This is how we investigate multilevel structures graphically for selected variables. It can be seen in the figure that the regions have different intercept and slope, suggesting that the effect of place of residence varies from one region to another. The same can be said for the educational level of mothers (Figure 3).

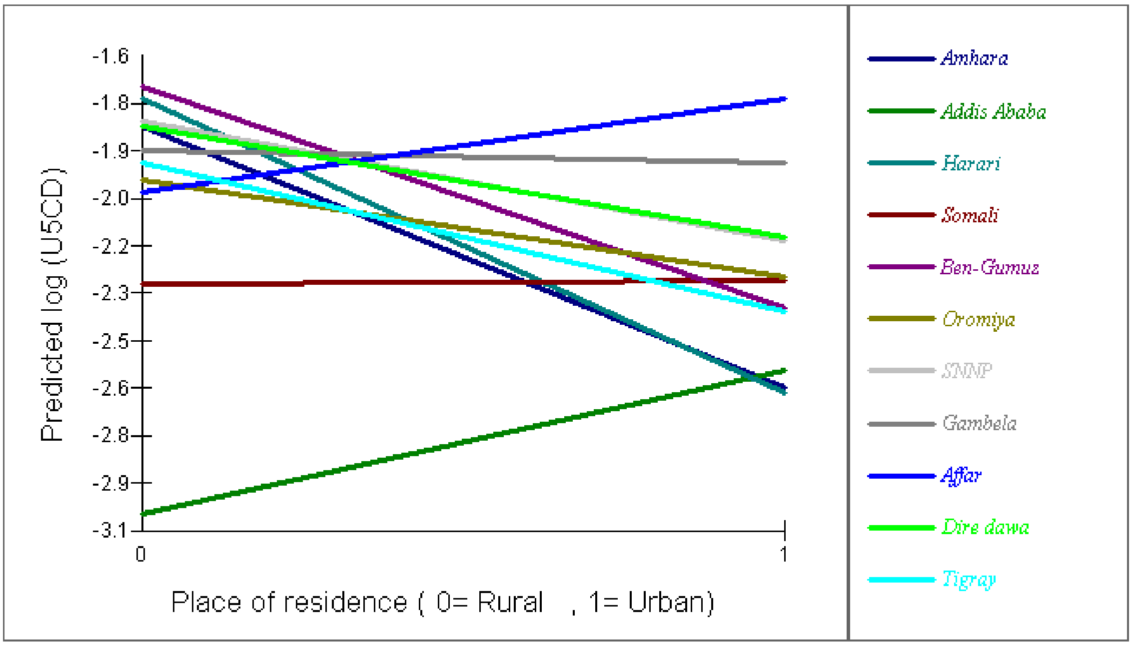

Figure 2: A plot of the predicted value of U5CD versus place of residence.

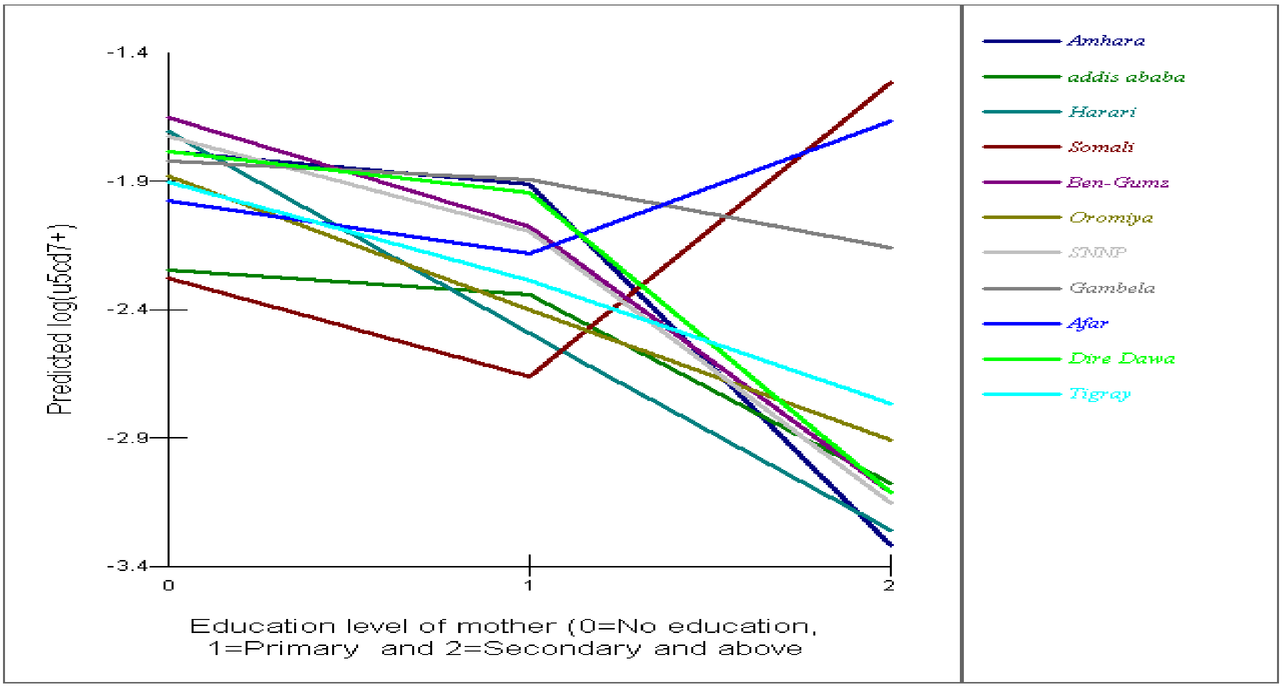

Figure 3: A plot of the predicted value of U5CD versus mother education level.

Generally, the lines in Figure 2 and 3 have different intercepts and slopes, and the steeper the slope the stronger will be the relationship between place of residence and U5CD per mother (for fig 2) or educational level of mother and U5CD per mother (for fig 3). The plots for the other predictors are shown in Appendix C.

The basic difference between the single level and multilevel model here is that the single level only tells whether there is a difference in under-five child mortality between regions (Table 4.4) while multilevel modeling reveals the magnitude of variation of U5CM from individual mothers and its significance between regions. Thus, investigating the existence and magnitude of U5CD variation among regions are our main subsequent task.

The analysis concerns a multilevel modeling of under-five child mortality determinants (risk factors) from individual mothers nested within 11 regions of Ethiopia under Poisson assumption. The results presented in the subsequent section are obtained using MLwiN for window.

4.3.2. Random intercept-only model

We first consider a random intercept only model in order to examine the variation due to the regional effects. The results presented in Table 4.5 indicate that there is a significant random variance among regions ($\hat{\boldsymbol{\sigma}}_{\boldsymbol{u0}}^{\mathbf{2}} = 0.14$, P-value <0.0001).

Table 4.5 Poisson multilevel Random intercept only model for the regional difference on U5CD.

Fixed effect	Estimate	se	exp(β)	P-value
β_0 *(constant)*	-1.934 *	0.02	0.1446	<0.0001
Random effect				
σ_{u0}^2 (between regions)	0.14*	0.021		<0.0001
Bayesian DIC		17218.61		

Note:*Significant (P-value <0.0001)

The inverse of the logarithm is used to interpret the results since the link between the expectation of dependent variable and the linear predictor is a logarithmic function. At the national level, on average, the number of U5CD per mother in all regions included in the study is 0.145 [exp (-1.934)].

4.3.3. The random intercept model

The next step in model fitting with this data is to add explanatory (predictor) variables in order to identify their effects on the response variable using Poisson regression model.

Various comparative statistics of the random intercept-only model (empty model) versus the random intercept model are shown in Table 4.6. The random intercept model with fixed explanatory variables is a better fit as compared to the empty model (χ^2_{cal}=16919.57 -16723.19=169.38 with p-value<0.0001).

Table 4.6 Comparisons of the DIC diagnostic between the random intercept-only model and random intercept models.

	Random intercept model	**Empty model**
Dbar (posterior mean of deviance)	16723.19	16919.57
Dthetabar(deviance evaluated at posterior mean)	16432.85	16619.73
pD (effective number of parameters)	290.34	299.83
DIC	17013.52	17218.61

The results from the random intercept model are given in Table 4.7. As can be seen from the table, under-five child death per mother is varying among regions. Since the level-two (region level) variance of the random intercept ($\boldsymbol{\sigma^2_{0u}}$) was found to be significant, this is an indication that the number of U5CD per mother differs among regions. In addition, educational levels of mother, place of residence, employment status of mother and age at first birth were also found to be significant determinants of under-five child death among the regions (p-values< 0.05).

Controlling for the effects of other variables and allowing the intercept parameter to vary across regions, the likelihood of U5CD for children born from mothers with no education and with primary education is about 2.5 and 1.9 times higher as compared to children born to mothers with secondary and higher education, respectively. The result also shows that the likelihood of U5CD is higher for children born to employed mothers as compared to those whose mothers are unemployed.

Table 4.7 Results of Poisson multilevel model with random intercept for the regional effect of mothers' characteristics on under-five child death.

Fixed effects		estimate	se	exp(β)	p-value
	β_0 *(constant)*	-2.914*	0.107	0.0543	<0.0001
Place of residence	*rural(ref)*			1	
	Urban	-0.117*	0.063	0.8896	0.0317
Education level of mother	*secondary and higher(ref)*			1	
	No education	0.932*	0.097	2.5396	<0.0001
	primary	0.644*	0.102	1.9041	<0.0001
Employment status of mother	*Non-working(ref)*			1	
	Working	0.132*	0.03	1.14110	<0.0001
Economic status	*Rich(ref)*			1	
	Poor	-0.079*	0.041	0.9240	0.0270
	Medium	0.006	0.04	1.0060	0.4404
Religion	*Muslim(ref)*			1	
	Orthodox	-0.059	0.038	0.9427	0.0602
	Others	-0.006	0.043	0.9940	0.4445
Source of water supply	*otherwise(ref)*			1	
	access to piped water	0.015	0.043	1.0151	0.3636
Availability of toilet facility	*otherwise(ref)*			1	
	if there is a toilet	0.023	0.037	1.0233	0.2671
Age at first birth	*age >=20(ref)*			1	
	age < 20	0.153*	0.036	1.1653	<0.0001
Random effects					
Level(regional effects)	$\boldsymbol{\sigma_{u0}^2}$	0.121*	0.02		<0.0001
Bayesian DIC	17013.52				

Note: ref = Reference categories. * Significant (P-value <0.05)

4.3.4. The random coefficients model

It is essential to determine whether the explanatory variables included in the study have different influence on the response variable (U5CM) among regions. A multilevel model with a random intercept and a random slope is therefore fitted.

Because of the limitations of MLwiN software, we will examine the influence of educational level of mothers; and health and environmental factors separately on U5CM between regions. Thus, two separate analyses will be conducted. Firstly, the effect of maternal education level (allowing it to randomly vary between regions) with other fixed effects (by setting the variance of other coefficients zero) on the number of U5CM is examined (table 4.8). Secondly, the effect of toilet facility and water supply (allowing them to randomly vary between regions) with other fixed effects (by setting the variance of other coefficients zero) on the number of U5CM is examined (table 4.9). Therefore, the table includes fixed effect coefficients and an overall (level-2) or regional variance constant term ($\boldsymbol{\sigma_{0u}^2}$) together with variance and covariance terms for their corresponding variables.

a. Models when coefficients of educational level of mothers vary

In comparison to the model with random intercept and fixed explanatory variables, the model with random intercept and random coefficients was found to be a best fit in explaining regional differences in under-five death per mother (χ^2_{cal}=16723.19 - 16604.6=118.55 with p-value<0.0001).

The results of fitted random intercept and random coefficient model are given in Table 4.8. According to the results, the overall region variance constant term, and the variance and the covariance terms for education level of mothers are found to be significant. The fixed effect of education level of mother, place of residence, employment status of mother, age at first birth and household economic status are significant (p-values<0.05) while religion of mother, toilet facility and source of water are found to be insignificant.

Table 4.8 Results of a Poisson multilevel model with random intercept and random coefficients for educational level of mother.

Fixed effects		estimate	se	exp(β)	P-value
	Intercept	-3.23*	0.123	0.0396	<0.0001
Education level of mother	no education	1.147*	0.111	3.1487	<0.0001
	primary	0.835*	0.117	2.3048	<0.0001
	secondary and above (ref)			1	
Place of residence	urban	-0.14*	0.063	0.8694	0.0131
	rural(ref)			1	
Religion	orthodox	-0.029	0.038	0.9714	0.2227
	Muslim(ref)			1	
	other wise	-0.02	0.047	0.9802	0.3352
Employment status	working	0.131*	0.031	1.1399	<0.0001
	not working (ref)			1	
Household economic status	poor	0.087*	0.044	1.0909	0.0240
	middle	0.089*	0.042	1.0931	0.01705
	rich (ref)			1	
Source water supply	piped water	0.016	0.041	1.0161	0.34819
	otherwise (ref)			1	
Availability of toilet facility	has toilet facility	-0.007	0.041	0.9930	0.43223
	otherwise (ref)			1	
Age at first birth	Age<20	0.145*	0.036	1.1560	0.0001
	Age>=20(ref)			1	
Random					
Level 2 (regional effects)					
	$(constant)\sigma_{u0}^2$	0.552*	0.13		<0.0001
	$(no\ education)\sigma_{u1}^2$	0.513*	0.147		0.0002
	$(primary)\sigma_{u2}^2$	0.282*	0.083		0.0003
	$(covariance)\sigma_{u01}$	-0.491*	0.13		0.0001
	$(covariance)\sigma_{u02}$	-0.339*	0.096		0.0002
	$(covariance)\sigma_{u12}$	0.351*	0.102		0.0003
Deviance		16604.64			
BDIC		16890.42			

Note: ref = reference categories. *Significant (P-value <0.05)

b. Models when coefficients of health and environmental variables vary

In comparison to the model with random intercept and fixed explanatory variables, the model with random intercept and random coefficients was found to have a better fit in explaining regional differences in under-five death per mother (χ^2_{cal}=102.04 with p-value<0.0001).

Table 4.9 shows that the overall region variance constant term and the variance for toilet facility and source of water are found to be significant. It is also noted that there is a significant covariance among intercept and slope. Both the covariance between the random intercept and the random slope for toilet facility and the covariance between the random intercept and the random slope for source of water show a negative sign, estimated as -0.049 and -0.043 respectively, suggesting that there is an inverse relation between the random intercept and the corresponding random slope. This indicates that regions with higher intercepts tend to have shallower slopes. This will lead to a fanning in pattern when we plot the regions predicted lines.

In general, the results of the multilevel Poisson regression suggest that there exists difference in the number of U5CM per mother among the regions in Ethiopia and the effect of educational level of mothers, toilet facility and source of water on U5CD per mother differs from region to region.

Table 4.9 Results of a Poisson multilevel model with random coefficients for source of water supply and toilet facility.

Fixed effects		estimate	se	exp(β)	p-value
	Intercept	-2.987*	0.109	0.0504	<0.0001
Education level of mother	no education	0.91*	0.089	2.4843	<0.0001
	Primary	0.626*	0.093	1.8701	<0.0001
	Secondary and above(ref)			1	
Place of residence	Urban	-0.173*	0.066	0.8411	0.0044
	rular(ref)			1	
Religion	orthodox	-0.038	0.039	0.9627	0.1649
	muslim(ref)			1	
	other wise	-0.026	0.048	0.9743	0.2940
Employment status	working	0.127*	0.031	1.1354	<0.0001
	not working (ref)			1	
Household economic status	poor	0.082*	0.046	1.0855	0.0373
	middle	0.082*	0.045	1.0855	0.0342
	rich (ref)			1	
water supply	piped water	0.007	0.05	1.0070	0.4443
	otherwise (ref)			1	
Availability of toilet facility	has toilet facility	0.011	0.048	1.0111	0.4094
	otherwise (ref)			1	
Age at first birth	Age<20	0.148*	0.036	1.1595	<0.0001
	Age>=20			1	
Random	Level 2 (regional effects)				
	$(constant)\sigma_{u0}^2$	0.105*	0.018		<0.0001
	Toilet(σ_{u5}^2)	0.065*	0.025		0.0047
	Water supply(σ_{u8}^2)	0.073*	0.03		0.0075
	$(covariance)\sigma_{u05}$	-0.049*	0.021		0.0098
	$(covariance)\sigma_{u08}$	-0.043*	0.019		0.0118
	$(covariance)\sigma_{u58}$	0.028*	0.025		0.1314
Deviance		16621.15			
BDIC		16898.4			

Note: ref = reference categories *Significant (P-value <0.05)

CHAPTER FIVE
DISCUSSION, CONCLUSION AND RECOMMENDATION

5.1. Discussion and Conclusion

The purpose of this paper was to examine the regional differences in under-five child death per mother in Ethiopia using single and multilevel count regression procedure. The study uses the 2005 demographic and health survey data to identify some of the factors that are responsible for regional differences in under-five child mortality.

Before the analysis of data using the Poisson approach, the basic assumption of the Poisson model, that is, equality of the mean and variance of the number of under-five death from individual mother, was tested. The results indicated that there was no over dispersion. Therefore, the final models are fit as Poisson linear model with a log link to accommodate the count nature of the response variable.

First, the preliminary single level (multiple Poisson) analyses show some interesting relationships between the regional variation of under-five child mortality and the selected explanatory variables.

In Ethiopia; Ben-Gumuz, SNNP and Amhara regions registered the highest under-five mortality risks. At the national level, the average number of U5CD from the individual mother in her lifetime was found to be 0.052 and this average has increased to 0.145 when regional variation is considered.

According to the results, mothers' education is an important socio-economic predictor of under-five child mortality, that is, mortality rate decreases with increase in mothers' education level. Many studies showed that the higher the level of maternal education, the lower the infant and child mortality. Caldwell

(1981) provided three explanations for the phenomenon: more educated mothers become less fatalistic about their children's illnesses, they are more capable of manipulating available health facilities and personnel and they greatly change the traditional balance of familial relationships with profound effects on childcare. In addition to these, they are more likely to have received antenatal care to give birth with some medical attendance, and to take their children at some time to see a physician. In this study, even after controlling for other variables, education of mother remained significant in the regression equations. This finding is consistent with Belaineh *et al.* (2007) and other studies.

With regard to level of urbanization, the results were unexpected. Theoretically, all things being equal, living in urban areas should be associated with a higher standard of living, better sanitation, and better health facilities, among other things. Although descriptive statistics results have revealed that mortality is higher in rural areas of Ethiopia, the effect is not statistically significant.

This study found that children born to very young (aged less than 20 years) mothers are more likely to die and these findings are consistent with Aguirre (1995) and Mondal *et al* (2009) findings.

Regarding sanitation, the findings indicated that the provision of piped water and toilet facility to households are insignificant. Such a situation may be due to interrelationship between covariates.

The study indicates that children born from working mothers have higher risk of mortality than non-working mothers. It was also found that under-five child mortality risk is lower for children of poor mothers compared to children of rich mothers. Although households' economic status is an important variable for reducing child mortality, in this study the variable is insignificant. This is quite unexpected, and might be due to poor data quality pertaining to classification of households' economic status as poor, medium and rich. This might also be due to the cross-sectional nature of the data and change in economic status of the household over time might be observed. Finally, religion of mothers remains a significant predictor of under-five child mortality.

Secondly, the Poisson multilevel model provided interesting relationships that would not be evident from a simple; single-level analysis. We showed that there is a significant variation of under-five mortality between regions. This may suggest differences in lifestyle, culture, ethnic or environmental determinants between different regions. Because of these potential cultural, socioeconomic and environmental differences, under-five child mortality exhibits a significant variation among regions of Ethiopia.

In the multilevel analysis, mothers are considered as nested within the various regions in Ethiopia. Three multilevel models: empty model, random intercept and random slope or random coefficient model were fitted in order to explain regional differences in the under-five mortality. The results obtained are discussed briefly below.

Before the analysis of data using the multilevel approach, the heterogeneity of the under-five mortality with regard to regions was checked. The plot of some selected variables shows that under-five mortality differs among regions. Such heterogeneity is a requirement in the multilevel analysis. Following this, a model without explanatory variables and three multilevel Poisson regression models were fitted for the national sample as a whole. In general, the fixed part of the effects of explanatory variables included in the models have somewhat similar interpretation as that of the multiple Poisson regression discussed above for the national level data. The random parts of the intercept and explanatory variables provided additional information. In all these models, the overall variance constant term was found to be statistically significant which may again imply differences in under-five mortality among regions of Ethiopia.

Due to restriction in the software, only the educational level of mother and environmental factors were analyzed separately. The effect of the random part of the constant (intercept) and educational level of mother; and the constant (intercept), source of water supply and toilet facility on under-five mortality differ across regions. Similarly, the interaction of the random parts for all factors provided significant effect on under-five mortality across regions.

5.2. **Recommendation**

Based on the results the following recommendations can be made:

- Educational level of mothers plays an important role in child survival. 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.
- Under-five mortality differentials per mother among regions are significant. This is an indication that the severity of U5CD varies from one region to another. Thus, in order to have a bearing on policy recommendations, future studies should focus on identifying risk factors of U5CD for each region of Ethiopia separately.

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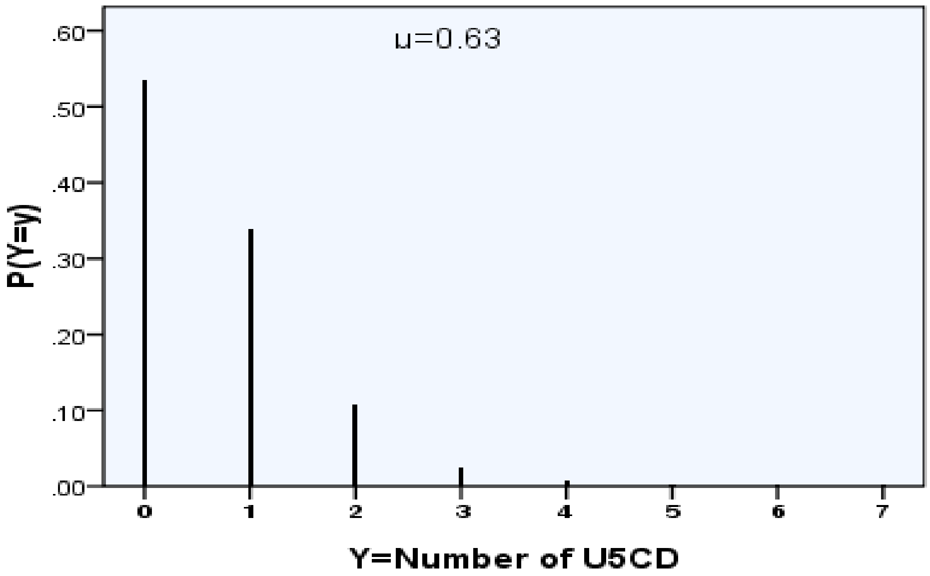
Appendixes

Appendix A.

Figure 1: Probability Density function of Poisson distribution



Appendix B.

Multiple Extra-Poisson regression model.

$$\text{U5CD+7}_i \sim \text{Poisson}(\pi_i)$$

$$\begin{aligned}\log(\pi_i) = {} & \text{offs}_i + -2.963(0.134)\text{CONS} + 0.279(0.097)\text{Amhara}_i + 0.208(0.110)\text{Harari}_i + -0.277(0.113)\text{Somali}_i + \\ & 0.354(0.102)\text{Ben-Gumz}_i + 0.118(0.096)\text{Oromiya}_i + 0.424(0.098)\text{SNNP}_i + 0.367(0.108)\text{Gambela}_i + 0.008(0.108)\text{Afar}_i + \\ & 0.233(0.106)\text{Dire Dawa}_i + 0.132(0.102)\text{Tigray}_i + 0.904(0.098)\text{no education}_i + 0.621(0.103)\text{primary}_i + \\ & -0.033(0.061)\text{Urban}_i + -0.130(0.040)\text{orthodox}_i + -0.221(0.047)\text{others}_i + 0.122(0.029)\text{working}_i + 0.011(0.041)\text{pipedwater}_i + \\ & -0.100(0.039)\text{poor}_i + -0.022(0.039)\text{middle}_i + 0.142(0.035)\text{age<20}_i + -0.057(0.038)\text{HAVE FACILITY}_i\end{aligned}$$

$$\text{var}(\text{U5CD+7}_i|\pi_i) = 1.027(0.015)\pi_i$$

variables		models					
		Poisson		Extra- Poisson		negative binomial	
		β	se(β)	β	se(β)	β	se(β)
	Intercept	-2.963	0.133	-2.963	0.134	-2.987	0.141
Region	Amhara	0.279	0.095	0.279	0.097	0.284	0.103
	Harari	0.207	0.108	0.207	0.11	0.188	0.118
	Somali	-0.277	0.111	-0.277	0.113	-0.26	0.12
	Ben-Gumuz	0.354	0.1	0.354	0.102	0.353	0.109
	Oromiya	0.118	0.095	0.118	0.096	0.126	0.102
	SNNP	0.424	0.097	0.424	0.098	0.425	0.104
	Gambela	0.367	0.106	0.367	0.108	0.372	0.115
	Afar	0.007	0.107	0.008	0.108	0.021	0.116
	Dire dawa	0.232	0.105	0.233	0.106	0.252	0.113
	Tigray	0.132	0.1	0.132	0.102	0.14	0.108
	ADDIS ABABA(ref)						
Educational level	no education	0.904	0.097	0.904	0.098	0.895	0.101
	primary	0.622	0.102	0.621	0.103	0.61	0.106
	Secondary and above(ref)						
Place of residence	urban	-0.033	0.063	-0.033	0.061	-0.034	0.066
	rural(ref)						
Religion	orthodox	-0.13	0.039	-0.13	0.04	-0.124	0.044
	Muslim(ref)						
	other wise	-0.221	0.047	-0.221	0.047	-0.21	0.052
Employment status of mother	working	0.122	0.028	0.122	0.029	0.129	0.032
	not working (ref)						
Water supply	piped water	0.011	0.04	0.011	0.041	0.003	0.045
	otherwise (ref)						
Household economic status	poor	-0.1	0.039	-0.1	0.039	-0.088	0.044
	middle	-0.022	0.038	-0.022	0.039	-0.015	0.043
	rich (ref)						
Age at first birth	age <20	0.142	0.035	0.142	0.035	0.141	0.038
	age>=20(ref)						
Toilet facility	has toilet facility	-0.057	0.037	-0.057	0.038	-0.055	0.041
	otherwise (ref)						
Over dispersion	alpha(α)	-	-	1.027	0.015	-	-

Table 1 (the above table) shows the comparison between Poisson, extra-Poisson and NB II regression models. This analysis obtained using RIGLS for sake of uniformity of the results. Since, currently MCMC not available in MLwiN for over-dispersed Poisson nor NB models.

Appendix C.

Predicted multilevel Poisson model when coefficients of place of residence vary

$$\mathrm{U5CD}_{ij} \sim \mathrm{Poisson}(\pi_{ij})$$

$$\begin{aligned}\log(\pi_{ij}) = {} & \mathrm{OFFS}_{ij} + \text{-}1.822(0.048)\mathrm{Amhara}_j + \text{-}3.047(0.488)\mathrm{Addis\ Ababa}_j + \text{-}1.734(0.104)\mathrm{Harari}_j + \text{-}2.321(0.088)\mathrm{Somali}_j + \\ & \text{-}1.696(0.070)\mathrm{Ben\text{-}Gumuz}_j + \text{-}1.990(0.049)\mathrm{Oromiya}_j + \text{-}1.809(0.048)\mathrm{SNNP}_j + \text{-}1.900(0.088)\mathrm{Gambela}_j + \\ & \text{-}2.032(0.079)\mathrm{Affar}_j + \text{-}1.824(0.132)\mathrm{Dire\ dawa}_j + \text{-}1.939(0.062)\mathrm{Tigray}_j + \text{-}0.823(0.208)\mathrm{Amhara.Urban}_{ij} + \\ & 0.455(0.496)\mathrm{Addis\ Ababa.Urban}_j + \text{-}0.932(0.189)\mathrm{Harari.Urban}_{ij} + 0.014(0.206)\mathrm{Somali.Urban}_{ij} + \\ & \text{-}0.699(0.293)\mathrm{Ben\text{-}Gumuz.Urban}_j + \text{-}0.306(0.157)\mathrm{Oromiya.Urban}_{ij} + \text{-}0.373(0.151)\mathrm{SNNP.Urban}_{ij} + \\ & \text{-}0.036(0.220)\mathrm{Gambela.Urban}_j + 0.296(0.210)\mathrm{Affar.Urban}_{ij} + \text{-}0.347(0.177)\mathrm{Dire\ dawa.Urban}_j + \\ & \text{-}0.468(0.230)\mathrm{Tigray.Urban}_j + u_{0j}\mathrm{CONS}\end{aligned}$$

$$\begin{bmatrix} u_{0j} \end{bmatrix} \sim \mathrm{N}(0,\ \Omega_u)\ :\ \Omega_u = \begin{bmatrix} 0.074(0.012) \end{bmatrix}$$

$$\mathrm{var}(\mathrm{U5CD}_{ij}|\pi_{ij}) = \pi_{ij}$$

Deviance(MCMC) = 16808.400(9210 of 9210 cases in use)

Predicted multilevel Poisson model when coefficients of health and environmental variables vary

$$\mathrm{U5CD7+}_{ij} \sim \mathrm{Poisson}(\pi_{ij})$$

$$\begin{aligned}\log(\pi_{ij}) = {} & \mathrm{OFFS}_{ij} + \beta_{0j}\mathrm{CONS} + 0.910(0.089)\mathrm{no\ education}_{ij} + 0.626(0.093)\mathrm{primary}_{ij} + \text{-}0.173(0.066)\mathrm{Urban}_{ij} + \\ & 0.148(0.036)\mathrm{age{<}20}_{ij} + \beta_{5j}\mathrm{ANYTOILET}_{ij} + 0.082(0.046)\mathrm{poor}_{ij} + 0.082(0.045)\mathrm{medium}_{ij} + \beta_{8j}\mathrm{piped}_{ij} + \\ & 0.127(0.031)\mathrm{working}_{ij} + \text{-}0.038(0.039)\mathrm{orthodox}_{ij} + \text{-}0.026(0.048)\mathrm{others}_{ij}\end{aligned}$$

$$\beta_{0j} = \text{-}2.987(0.109) + u_{0j}$$

$$\beta_{5j} = 0.011(0.048) + u_{5j}$$

$$\beta_{8j} = 0.007(0.050) + u_{8j}$$

$$\begin{bmatrix} u_{0j} \\ u_{5j} \\ u_{8j} \end{bmatrix} \sim \mathrm{N}(0,\ \Omega_u)\ :\ \Omega_u = \begin{bmatrix} 0.105(0.018) & & \\ \text{-}0.049(0.021) & 0.065(0.025) & \\ \text{-}0.043(0.019) & 0.028(0.025) & 0.073(0.030) \end{bmatrix}$$

$$\mathrm{var}(\mathrm{U5CD7+}_{ij}|\pi_{ij}) = \pi_{ij}$$

Deviance(MCMC) = 16621.150(9210 of 9210 cases in use)

Multilevel Poisson model when coefficients of educational level of mothers vary

$$\mathrm{U5CD7+}_{ij} \sim \mathrm{Poisson}(\pi_{ij})$$

$$\begin{aligned}\log(\pi_{ij}) = {} & \mathrm{OFFS}_{ij} + \beta_{0j}\mathrm{CONS} + \beta_{1j}\mathrm{no\ education}_{ij} + \beta_{2j}\mathrm{primary}_{ij} + -0.140(0.063)\mathrm{Urban}_{ij} + 0.145(0.036)\mathrm{age{<}20}_{ij} + \\ & -0.007(0.041)\mathrm{ANYTOILET}_{ij} + 0.087(0.044)\mathrm{poor}_{ij} + 0.089(0.042)\mathrm{medium}_{ij} + 0.016(0.041)\mathrm{piped}_{ij} + \\ & 0.131(0.031)\mathrm{working}_{ij} + -0.029(0.038)\mathrm{orthodox}_{ij} + -0.020(0.047)\mathrm{others}_{ij}\end{aligned}$$

$$\beta_{0j} = -3.230(0.123) + u_{0j}$$

$$\beta_{1j} = 1.147(0.111) + u_{1j}$$

$$\beta_{2j} = 0.835(0.117) + u_{2j}$$

$$\begin{bmatrix} u_{0j} \\ u_{1j} \\ u_{2j} \end{bmatrix} \sim \mathrm{N}(0,\ \Omega_u)\ :\ \Omega_u = \begin{bmatrix} 0.552(0.130) & & \\ -0.491(0.130) & 0.513(0.147) & \\ -0.339(0.096) & 0.351(0.102) & 0.282(0.083) \end{bmatrix}$$

$$\mathrm{var}(\mathrm{U5CD7+}_{ij}|\pi_{ij}) = \pi_{ij}$$

Deviance(MCMC) = 16604.640(9210 of 9210 cases in use)

Appendix D Prediction: Visualizing the model

The prediction equation for a particular predictor x can be Written as:

$$\log(\hat{y}_{ij} = \widehat{U5CD}) = \hat{\beta}_0 + \hat{\beta}_1 X_{1ij} + \hat{\mu}_{0j} + \hat{\mu}_{1j} X_{1ij}$$

Adding in region level variance μ_{1j} and μ_{0j} gives separate region lines.

The predicted value of U5CD model for age at first birth

$$\mathrm{U5CD}_{ij} \sim \mathrm{Poisson}(\pi_{ij})$$

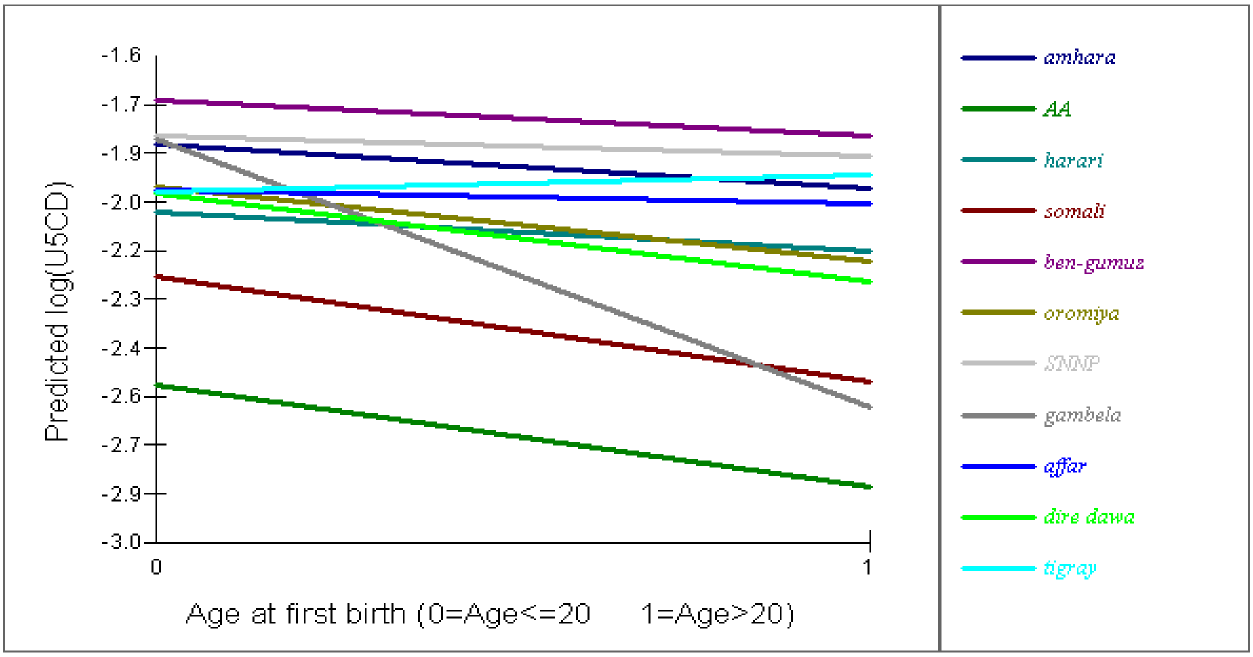
$$\begin{aligned}\log(\pi_{ij}) = {} & \mathrm{OFFS}_{ij} + -1.853(0.051)\mathrm{amhara}_j + -2.547(0.101)\mathrm{AA}_j + -2.049(0.101)\mathrm{harari}_j + -2.234(0.092)\mathrm{somali}_j + \\ & -1.728(0.074)\text{ben-gumuz}_j + -1.976(0.050)\mathrm{oromiya}_j + -1.829(0.051)\mathrm{SNNP}_j + -1.839(0.084)\mathrm{gambela}_j + \\ & -1.986(0.083)\mathrm{affar}_j + -1.993(0.096)\text{dire dawa}_j + -1.991(0.065)\mathrm{tigray}_j + -0.126(0.098)\text{amhara.age>=20}_{ij} + \\ & -0.293(0.187)\text{AA.age>=20}_{ij} + -0.112(0.159)\text{harari.age>=20}_{ij} + -0.305(0.146)\text{somali.age>=20}_{ij} + \\ & -0.100(0.149)\text{ben-gumuz.age>=20}_{ij} + -0.215(0.083)\text{oromiya.age>=20}_{ij} + -0.059(0.074)\text{SNNP.age>=20}_{ij} + \\ & -0.771(0.226)\text{gambela.age>=20}_{ij} + -0.040(0.120)\text{affar.age>=20}_{ij} + -0.259(0.170)\text{dire dawa.age>=20}_{ij} + \\ & 0.051(0.110)\text{tigray.age>=20}_{ij} + u_{0j}\mathrm{CONS}\end{aligned}$$

$$\left[u_{0j}\right] \sim \mathrm{N}(0,\ \Omega_u)\ :\ \Omega_u = \left[0.085(0.013)\right]$$

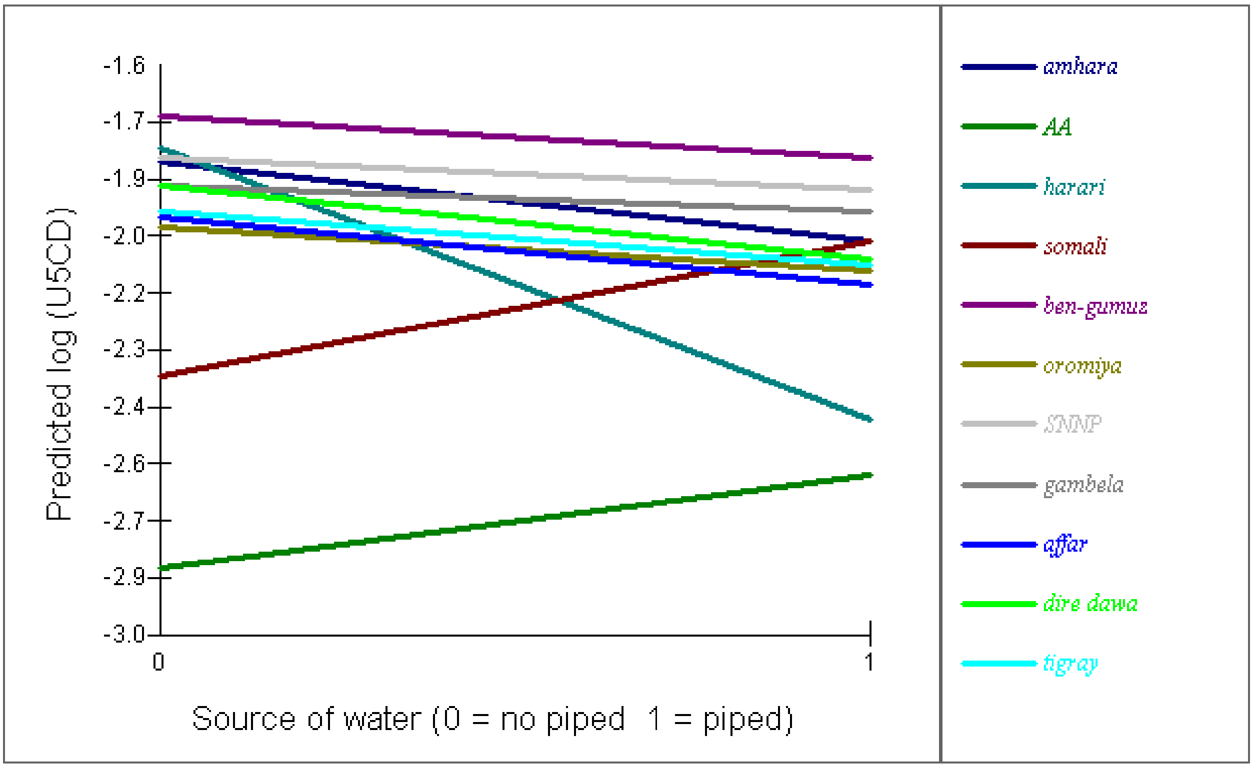
$$\mathrm{var}(\mathrm{U5CD}_{ij}|\pi_{ij}) = \pi_{ij}$$

Deviance(MCMC) = 16817.000(9210 of 9210 cases in use)

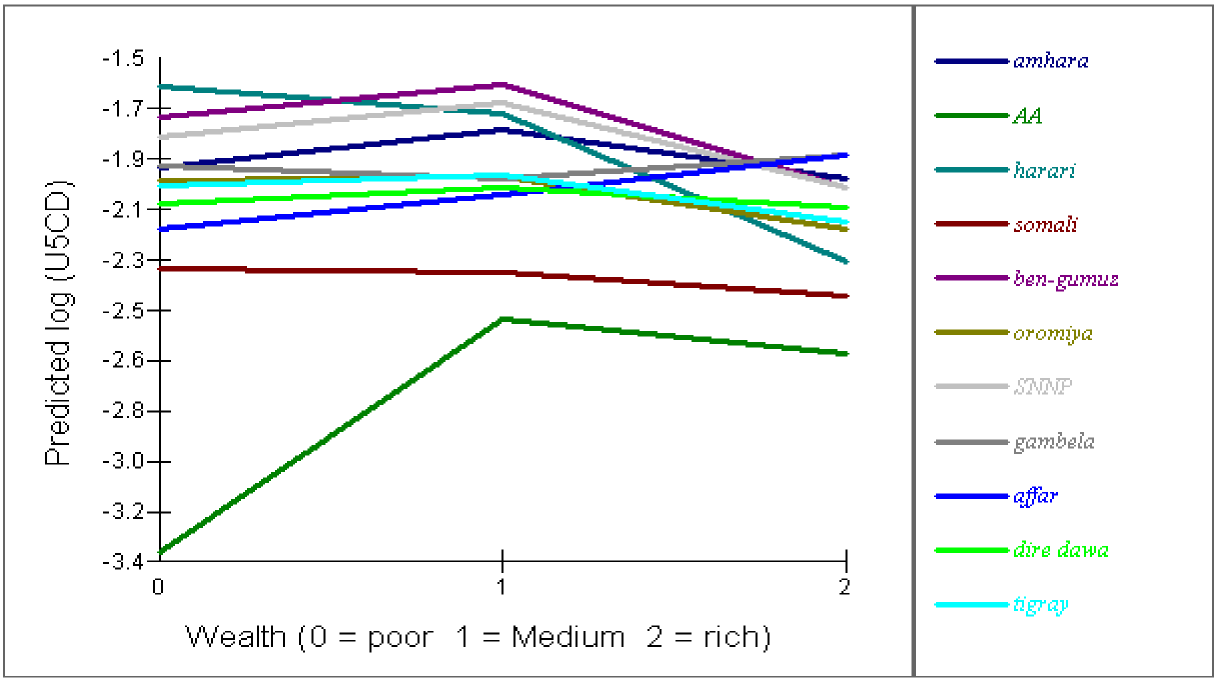
A plot of the predicted value of U5CD versus age at first birth.



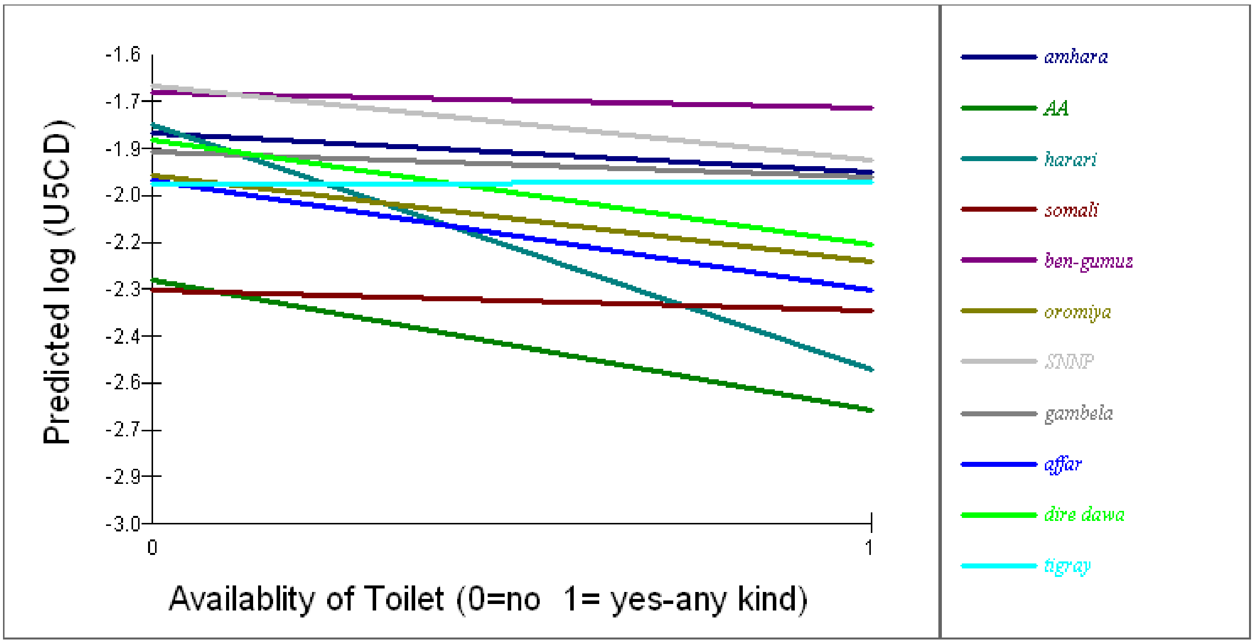
A plot of the predicted value of U5CD versus source of water supply



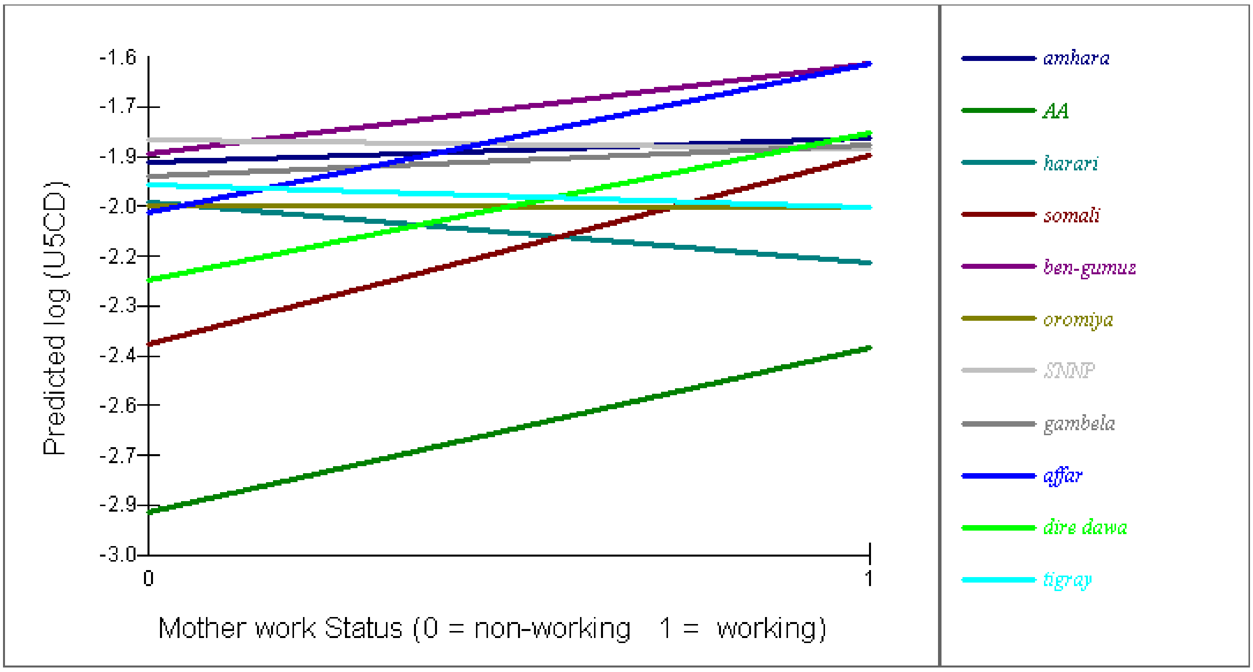
A plot of the predicted value of U5CD versus Economic status of mother



A plot of the predicted value of U5CD versus availability of Toilet



A plot of the predicted value of U5CD versus mother work status



A plot of the predicted value of U5CD versus religion