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HABITU, LIYEW

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DEPARTMENT OF STATISTICS
BAHIR DAR UNIVERSITY

FACTORS INFLUENCING DESIRED NUMBER OF CHILDREN AMONG ETHIOPIAN WOMAN. APPLICATION OF COUNT REGRESSION MODELS.

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A THESIS SUBMITTED TO THE DEPARTMENT OF STATISTICS IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTERS OF SCIENCE IN STATISTICS (BIOSTATISTICS)

JUNE 2018

ETHIOPIA, BAHIR DAR

DECLARATION

I, the undersigned, declare that the thesis **Factors influencing desired number of** children among Ethiopian woman: application o is my original work, has not been presented for degree or diploma in this or any other University and all sources of materials used for the thesis have been duly acknowledged.

Name: Habitu Liyew

Signature: ___________________________

Place of submission: Department of statistics, Bahir Dar University

Date of submission: June 2018

APPROVAL SHEET

This is to certify that the thesis entitled ñ**Factors influencing desire**

among Ethiopian woman: application of count regression modelsò submitted in partial fulfillment of the requirements for the degree of Master of Science in Statistics (Biostatistics), to the Department of Statistics, Bahir Dar University, is a record of original research carried out by Habitu Liyew under my supervision and no part of the thesis has been submitted for any other degree or diploma in this or other universities. The assistance and help received during the course of this investigation have been acknowledged. Therefore, I recommend that the thesis would be accepted as partial fulfillment of the requirement for the Master of Science degree in Statistics (Biostatistics).

Name of advisor	**Date**	**Signature**

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ABSTRACT

Fertility is one of the elements in population dynamics that has a significant contribution towards changing population size and structure over time. Fertility preference, defined as desired family size or the ideal number of children is known to have impacts on the total fertility rate and hence on the population size and structure. The main objective of this study was to identify the most important factors affecting desired number of children among Ethiopian women at reproductive age. The study was based on the 2016 Ethiopian demographic and health survey data (EDHS). Count regression models were used to model the desired number of children among women in Ethiopia. Results showed that the mean number of children per women was high among aged mothers, less educated mothers, mothers from rural areas, women in the poorest economic level and woman having no work. The highest average desired number of children was recorded in Somali region (10.58) and the lowest in Addis Ababa city administration (3.56). The Negative Binomial regression model was found to be the most appropriate model for the data. The random intercept Negative Binomial regression model showed that Womenôs age, Household head, Co *education, Religion, Marita*l status, Husbandôs work, Family s *significant predictors of the desired number of children by women at reproductive age. The study also showed that there was a significant regional variation in desired number of children among Ethiopian women.*

Key words: *Fertility rate, Desire number of children, statistical weight, EDHS, Count Regression models, multilevel analysis.*

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List of Abbreviations

AIC	Akaike Information Criteria
BIC	Bayesian Information Criteria
CSA	Central Statistical Agency
DNC	Desired Number of Children
EA	Enumeration Area
EDHS	Ethiopian Demographic and Health Survey
EPHI	Ethiopian Public Health Institute
FMoH	Federal Ministry of Health
GLMs	Generalized Linear Models
ICF	International Consultancy Fund
IUD	Intrauterine Device
LRT	Likelihood Ratio Test
ML	Maximum Likelihood
NGOs	Non-Governmental Organizations
NB	Negative Binomial
SNNPE	South Nation Nationalities and Peoples of Ethiopia
TFR	Total Fertility Rate
UNFPA	United Nations Population Fund
UNICEF	United Nations International Children Fund
USAID	United States Agency for International Development
IRR	Incidence Rate Ratio

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the Study

Fertility is one of the elements in population dynamics that has significant contribution towards changing population size and structure over time. Fertility and future projected population growth are much higher in sub-Saharan Africa than in any other region of the world (Bongaarts, 2008; Casterline, 2001). About eight percent of the world
countries that have experienced only limited fertility decline to date. In these countries the average woman has five or more children over her lifetime. Most of these countries are in sub-Saharan Africa (Organization, 2015).

In 1970's Ethiopia has experienced a very high rate of population growth as in other developing countries. The countryôs populat (Setegn, Lakew, 2016 w
& Deribe, 2016), placing it as the second most populous nation in sub-Saharan Africa. According to EDHS, fertility declined only slightly between 2000 and 2005, from 5.5 children per woman to 5.4, and then decreased further to 4.8 children in 2011 and 4.6 children per woman in 2016. Overall, the total wanted fertility rate (TWFR) in Ethiopia is 3.0 children per woman in 2000 to 2.3 children in 2016. All the efforts to control higher population growth become useless when the household desire larger number of children (Tiruneh, Chuang, Ntenda, & Chuang, 2016).

A large proportion of Ethiopians, regardless of their number of living children, consider four or more children to be desired. Women desired family size of 4.5 children, and men prefer 4.6 children in 2016. Womenôs desired family size has declined in the last ten years, from 5.3 children in 2000 to 4.5 children in 2005 and 4.3 children in 2011 and slight increasing in 2016 from 4.3 to 4.5. And menôs desired family size has declined in the last ten years, from 5.3 children in 2000 to 5.2 children in 2005 and 4.8 children in 2011 and 4.6 in 2016.

Some studies have mentioned the importance of the role of men in reproductive health and their influence on the decision-making and behavior related to reproduction (Dudgeon & Inhorn, 2004; Greene, 2000). As mentioned, many family planning programs have focused mainly on women. Even though men are increasingly being involved by reproductive health programs, the view of men still seem to be that they are peripheral and problematic (Greene, 2000). (Short &

Kiros, 2002) studied fertility preferences and demands for contraception in Ethiopia. The authors reported a gender difference between husbands and wives in fertility desires; husbands were more Pronatalist than their wives. (Lasee & Becker, 1997) studied husband-wife communication related to family planning and the use of contraceptives in Kenya. The authors reported that the
wifeôs perception of her husbandôs approval o on the
current contraceptive use. The result shows
reproduction have a strong impact on womenô
Therefore, it is important to study both gend productive, as well as the
communication between wife and husband, in order to understand what factors shape their behavior.

The information pertaining to desired family size has been gathered in fertility related surveys in Ethiopia, an assessment of these variables as the factors influencing the achieved family size remains problematic. Keeping in view the fact that the process of family size regulation requires the motivation and use of family planning methods, for which education is a closely related variable, one has to be careful in drawing any inference about the linkages between the desired family size and actual family size. In this connection, it has to be kept in view that the number of living children a woman has at a given time is not only the product of her reproductive behavior, but also of the risks of mortality through which the children ever-born pass overtime. To the extent that the rise in survival probabilities owing to decline in child mortality is not internalized by the parents in their reproductive norms, an excess of living children over the desired number appears to be an obvious outcome. Such a non-correspondence is also driven in case the son preference is operative (Bhargava, 2007).

Several studies investigated factors that affect desired family size using some statistical methods such as logistic regression model and count regression model: (Setegn et al., 2016) aimed to determine desired family size and identify factors that influence family size among residents of Assela town, Ethiopia by using logistic regression model. (Heer & Smith, 1968) adopted a generalized linear model (GLM) with a natural log- link function - Poisson regression.

1.2 Statement of the Problem

As shown in the background information, Ethiopia has a rapid population growth. The Ethiopian government and international organizations have tried to reduce the pace of growth by education in family planning and providing contraceptives. Despite these efforts, there is still a higher fertility rate than what is considered. Fertility behavior influences population growth, it has consequences on resources, employment situation, health and other social facilities. The mechanism of factors affecting fertility is that intermediate variables influence fertility directly, while socio-economic and demographic variables affect fertility indirectly through intermediate variables (Bongaarts, 1978). Some of these factors could be literacy status, occupation, religion, child birth- death ratio, wealth status, place of residence, household headship, contraceptive use, region, reproductive life span, age at first marriage and desired number of children (Angeles, 2010; Wolfe & Behrman, 1992).

Several studies investigated determinants of desired family size in Ethiopia using some set of variables and statistical methods such as logistic regression, survival analysis and Poisson regression models (Long & Freese, 2006). Since, the desired number of children (DNC) data is a count data, Poisson Regression Models (PRM) and Negative Binomial Regression Models (NBRM) have been shown to be statistically more appropriate (Poston Jr, 2002).

This study was aimed to assess the desired number of children and the potential factors influencing desired number of children by women at reproductive age using appropriate count regression models. Since the fertility level in Ethiopia is 4.6 children per woman and some policy makers are worried about the high fertility rate (EDHS, 2016).

1.3 Objectives of the Study

1.3.1 General Objective

The main objective of this study was to identify socio-economic and demographic factors associated with the desired number of children among Ethiopian women of reproductive age (15-49).

1.3.2 Specific Objective

- Estimating the average desired number of children among Ethiopian women of reproductive age.
- Compare and contrast statistical results of desired number of children of women among Regions, Age groups, Urban and Rural areas and different segments of population.

- Apply single and multilevel count regression models for analyzing determinant factors for desired number of children of women in Ethiopia.
- To explore how a variety of cultural, social and structural factors influence desired number of children among Ethiopian women.

1.4 Significance of the Study

It is hoped that findings from this research can be useful in many ways.

- Expected to contribute by filling the information gap concerning the impact of factors that affect desired number of children in Ethiopia.
- The findings are believed to be useful for policy making, monitoring and evaluation activities of the government and different concerned agencies.
- The study was also expected to add to the body of knowledge on fertility and reproductive health issues in Ethiopia.
- Finally, the study could be a stepping stone for further studies.

1.5 Limitation of the study

- The study uses reported characteristics of mothers and households that may vary with time. Only motherôs age is fixed, others -varying covariates. However, in our analysis all covariates were considered fixed during the study period.
- The desired number of children in terms of sex was not included, thus further studies may consider the sex composition of desired family size as response variable.
- The single negative binomial and multilevel random intercept model is failing to convergence because of a large number of parameter estimates due to in inability of computer computing capacity. Thus, here, we did not see the interaction effect of the predictors.

1.6 Organization of the Thesis

This thesis has been organized as follows. In Chapter 1, the background, statement of the problem, objective, its significance and limitation of the study are presented. The second Chapter provides the literature review. The data source, methodology and the research hypotheses are given in Chapter three. The fourth Chapter covers the analysis, findings of the research and discussion. Finally, conclusions and recommendations are made in Chapter five.

CHAPTER TWO

LITRATURE REVIEW

2.1 General Over View

Desired family size is simply the number of c (Uddin, Bhuyan, & Islan, 2011). Like other fertility preferences, it is not fixed but changes over the family life course in respect to actual fertility experiences and outcomes (Namboodiri, 1972). Desired family size is one of several related concepts regarding family size preferences (intended family size, desired family size and preferred number of children) (Coombs, 1974), refers to it as a personal ideal. Although the concepts are sometimes used interchangeably, no distinguishable difference among the concepts in terms of measuring orientation to number of children have been found (Olaleye, 1993). A major critique, though, is that desired family size measures opinion rather than intentions (Olaleye, 1993), and it is fraught with high desired family size responses from women with high fertility by older women and non-numeric responses (Bongaarts, 2011) that are given by women who are likely to desire large family size (Bongaarts, 2011; Olaleye, 1993) however, asserts that further insight could be gained in addressing the issue of high fertility by studying desired family size as the dependent variable. (Cleland & Wilson, 1987) also suggest that examination of fertility preferences such as desired family size can give insight into ideational influences that are based on social and psychological factors. Desired family size is an expression of fertility intentions which can lead to fertility limiting behavior (Harbour, 2011).

Desired family size can take many forms. (Thomson & Brandreth, 1995) refers to desired family size as the number of children wanted in one
children. (McClelland, 1983) defines desired family size as the number of children parents would have if there were no subjective or economic problems involved in regulating fertility. Although important reductions in total fertility have taken place around the world and some authors find that in many countries total fertility is below the replacement levels. However, there are countries where a considerable proportion of unintended children still exist. Within the context of a particular number of total children desired, parents may desire at least one child of each sex, a minimum number of children of a particular sex, or appropriately equal numbers of sons and daughters. Thus, couples may continue to give birth beyond their desired family size in order to

achieve a favorable number of distribution of sons and daughters. A higher proportion of couples who achieve their preferred sex composition of children do not want more children. Couples who have either all sons or all daughters are more prone to have additional children to fulfil their desire in respect of sex preference. However, those who have children of both sexes, do not desire more babies (Cleland, Verrall, & Vaessen, 1983).

Fertility is one of the elements in population dynamics that has a significant contribution towards changing population size and structure over time. Fertility rate is the number of children born per couple, person or population. Differential in fertility behavior and fertility levels in different areas and among population strata or characteristics have been among the most pervasive findings in demography (Adhikari, 2010). It is also a complex variable affected by multiple factors. According to (Bongaarts, 1978), factors affecting fertility are broadly classified into proximate (direct) and distal (indirect) factors. The proximal factors are bio-behavioral factors, like being sexually active, use of contraceptive, duration of postpartum in fecund ability, abortion and sterilizing which affect fertility directly, whereas, distal determinant are socio-cultural factors which affect fertility indirectly through affecting the bio-behavioral factors.

Fertility desires or preferences capture how individuals rank different fertility sizes given their relative assessment of the net benefits assoc

or desired fertility then captures the number of children a woman would choose to have at the time of the survey, based on her assessment of the costs and benefits of childbearing and with complete control over her fertility (Bongaarts, 1991; Easterlin, 1978; McClelland, 1983). Several theories regarding the determinants of wanted fertility have been proposed. Since they provide important theoretical background for formulating hypotheses regarding the stability of individualsô stated fertility and the p ident

According to (Burleson, 2005) development is the best contraceptive and that family planning programs are of little values in bringing about in changing the unwanted fertility.

Fertility intentions, if not ideals, hold the promise that actual fertility could mirror intentions over the long run, thus bringing observed fertility closer to replacement. Consistent with this view (Bongaarts, 2002), argues that a substantial part of the discrepancy between aggregate fertility intentions and contemporary fertility levels can be accounted for by timing shifts, specifically the postponement of childbearing to later ages. Once this postponement abates, as it eventually must, intentions and current behaviors will be more similar. In addition, frustrated demand for children could encourage institutional adjustments that would allow childbearing to correspond to levels desired by women and couples, again raising fertility to levels that approximate intentions.

2.2 Empirical Studies

Study conducted by (Calhoun, Nanda, Speizer, & Jain, 2013), examines the effect of family sex composition on fertility desires and family planning behaviors in urban Uttar Pradesh, India. Multivariate analysis was used to examine the association between family sex composition and fertility desires and FP use. The Multivariate results indicate that family sex composition is associated with fertility desires and FP use.

Study by (Adhikari, 2010), examines Demographic, socio-economic, and cultural factors affecting fertility differentials in Nepal. This paper has used data from the Nepal Demographic and Health Survey (NDHS 2006). The analysis was confined to ever married women of reproductive age. Both Bivariate and multivariate analyses have been performed to describe the fertility differentials. The bivariate analysis was applied to examine the association between children ever born and women's demographic, socio-economic, and cultural characteristics. Besides bivariate analysis, the net effect of each independent variable on the dependent variable after controlling for the effect of other predictors has also been measured through multivariate analysis. There were considerable differentials in the average number of children ever born according to women's demographic, socio-economic, and cultural settings. Regression analysis revealed that age at first marriage, perceived desired number of children, place of residence, literacy status, religion, mass media exposure, use of family planning methods, household headship, and experience of child death were the most important variables that explained the variance in fertility.

Study by (Upadhyay & Karasek, 2012), examines on womenôs empowerment and family size. The analysis used couples data from DHS surveys in four Sub-Saharan African countries: Guinea, Mali, Namibia and Zambia. Womenôs emp by participation in household decision making, attitudes toward wife, beating and attitudes toward refusing sex with oneôs husband. Multivariable was used to model number of womenôs children, and multivariable logistic regression analysis was used to mode having more children than their desired. In Guinea and Zambia, negative attitudes toward wife

beating were associated with having a smaller desired number of children. Greater household decision making was associated with a smaller desired number of children only in Guinea. Additionally, household decision making and p
sex were associated with elevated odds of having more children than desired in Namibia and Zambia, respectively; negative attitudes toward wife beating were associated with reduced odds of the outcome in Mali. Womenôs empowerment a
is not consistently associated with a desire for smaller families or the ability to achieve desired fertility in these Sub-Saharan African countries.

Study by (Puurbalanta & Aselisewine, 2016) using Poisson regression model analysis examines desired family size in Ghana. This study was a cross-sectional study through primary data analysis. A metropolitan representative sample size of 511 respondents age 16 years and above in the Tamale metropolis was interviewed. The different categories of people at different locations sampled the use of stratified sampling. It was shown that males preferred large family size to females in any defined number of children per family. Closer relationships were also identified between desired family size and sex of respondents, educational attainment of respondents, type of marriage and preferred s

Study by (Muhoza, Broekhuis, & Hooimeijer, 2014) aimed to determine variations in desired family size and excess fertility in east Africa. The data for this study are drawn from the Kenya 2008/9, Tanzania2005, Rwanda 2010, and Uganda 2011Demographic and Health Survey data sets. As this study was restricted to married women or women living in a consensual union who have at least one child and reported numerical responses to the question about desired family size. Binary Regression Estimation Model was used as a method of data analysis and as a result there was variations of desired fertility in terms of desired number of children. T
are largest in Kenya and smallest in Rwanda, while Tanzania and Uganda occupy intermediate positions.

Study by (Matovu, Makumbi, Wanyenze, & Serwadda, 2017), Examines on determinants of fertility among married or cohabiting individuals in Rakai, Uganda: a cross- sectional: a cross-sectional study. This cross-sectional study of fertility desire (desire to have another child) was nested in a cluster randomized demand creation intervention tri
HIV counseling and testing uptake among married or cohabiting individuals that was conducted

in Rakai district. Data were collected on socio-demographic, behavioral and fertility related characteristics. They used a modified Poisson regression model to generate prevalence ratio as a measure of association for factors that were independently associated with fertility desire. Overall, fertility desire was higher in men than women. After adjusting for potential and suspected cofounders, the factors that were negatively associated with fertility were age. Being male, having primary education and having not yet attained the desired family size were positively associate with fertility desire.

A research conducted by (Ayele, 2015) using the 2011 Ethiopian demographic and health survey found that materials used for roof, wall and floor, family size and births in the last five years were found to have a significant relation to fertility level of women in the last five years. Significant variation in fertility level was also observed among rural and urban residents of Ethiopia.

CHAPTER THREE

METHODOLOGY

3.1 Source of Data

This study utilizes the 2016 Ethiopian Demographic and Health survey (EDHS) data. The 2016 Ethiopia Demographic and Health Survey (EDHS) was the fourth survey implemented by the Central Statistical Agency (CSA). The CSA has conducted the survey in collaboration with the Federal Ministry of Health (FMoH) and the Ethiopian Public Health Institute (EPHI) with technical assistance from ICF International, and financial as well as technical support from development partners. The survey was conducted from January 18, 2016, to June 27, 2016, based on a nationally representative sample that provides estimates at the national and regional levels and for urban and rural areas. The survey target groups were women age 15-49 and men age 15-59 in randomly selected households across Ethiopia. A total of 18,008 households were selected for the sample of which 17,067 were occupied. Of the occupied households, 16,650 were successfully interviewed, yielding a response rate of 98%. From the total 15,683 women who were interviewed, this study consider a total of 13,941 women. The rest 1742 women include in the study because of non-numeric response for desired number of children.

3.2 Variables Include In the Study

3.2.1 Response Variable

The response variable of this study (Y_i) is a count variable, the total number of desired children a woman at the reproductive age (15-49) would like to have in her lifetime, $Y_i = 0, 1, 2, \ldots$ where i refers to the individual mother.

3.2.2 Predictor Variables

Factors included as potential predictors of desired number of children by women at reproductive age (15-49) are presented below in table 3.1.

Table 3. 1 predictor variables

Predictor variables	Representation of variable	Category
Region	X_1	1=Tigray
		2=Afar
		3=Amhara
		4=Oromia
		5= Somali
		6= Benshangul G.
		7= SNNPE
		8= Gambela
		9= Harari
		10= Addis Abeba
		11= Dire Dawa
Womenôs age	X_2	1=15-19
		2=20-24
		3=25-29
		4=30-34
		5=35-39
		6=40-44
		7=45-49
Household head	X_3	1=Male
		2=Female
Womenôs living	X_4	1=No
		2=Yes
Contraception using	X_5	1=No
		2=Yes
Place of residence	X_6	1= Urban
		2= Rural
Wealth index	X_7	1= Poorest
		2= poorer
		3= Middle
		4= Richer
		5= Richest
Womenôs employ	X_8	1= Not Employed
		2= Employed
Womenôs educat	X_9	1= No education
		2= Primary
		3= Secondary
		4= Higher
Religion	X_{10}	1= Orthodox
		2=Catholic
		3= Protestant
		4= Muslim
		5= Traditional
		6= Other
Marital status	X_{11}	1= Single
		2= Married
		3= Separated
Husbandôs educ	X_{12}	1= No education
		2= Primary
		3= Secondary
		4= Higher
		5= Donôt kno
Husbandôs empl	X_{13}	1= Not Employed
		2= Employed
		3= Donôt Know
Family size	X_{14}	Continuous
Age at first marriage	X_{15}	Continuous

3.3 Methods of Data Analysis

3.3.1. Design weights

The weights are used primarily in order to make the computed statistics based on the gathered data more representative of the population from which the data are retrieved. Weights are often fractions, always positive and nonzero (Little & Vartivarian, 2005). Generally, Weighting is a necessary process that guarantees unbiased estimates for population parameters in complex study settings, equally representative for every individual within a sampling stratum, Weighting brings the sample population to the same scale of the target population with design weight, weighting keeps the sample distribution close to the distribution of the target population, especially when oversampling is applied in certain areas, reduced sampling errors and Weighting for correcting nonresponse (DuMouchel & Duncan, 1983).

The design weights are used either when we want the survey statistics to be representative of the underlying population or when we want to compensate for over or under-sampling of specific cases or for disproportionate stratification. For computing design weights, we must know the sampling fraction, which is usually the over-sampling or the under-sampling amount for a given group or area. Thus, for instance, the unweighted samples in a survey over or under-represent people of certain areas or size of households, such as those in larger households. The design weight corrects for differences in selection probabilities, thereby making the sample more representative of a true sample of individuals in a country. The design weights are computed as normalized inverse of the inclusion probabilities. That is, if we know the sampling fraction of each respondent to the survey, then the weight is the inverse of the sampling fraction (Johnson, 2008).

3.3.1.1 Sampling Weight Methodology of women in EDHS

Due to the non-proportional allocation of the sample to different regions and their urban and rural areas and the possible differences in response rates, a sampling weight must be used in all analyses using the 2016 EDHS data to ensure the actual representative of the survey results at both the national and domain levels. Since the 2016 EDHS sample is a two-stage stratified cluster sample, sampling weights are based on sampling probabilities separately for each sampling stage and each cluster. We use the following notations (EDHS, 2016):

P_{1hi}: First-stage sampling probability of the i^{th} cluster in stratum h

P_{2hi}: Second-stage sampling probability within the i^{th} cluster (household)

Let a_h be the number of EAs selected in stratum h, M_{hi} the number of households according to the sampling frames in the i^{th} EA, and $\sum M_{hi}$ the total number of households in the stratum. The probability of selecting the i^{th} EA in the 2016 EDHS sample is calculated as:

$$\frac{a_h M_{hi}}{\sum M_{hi}}$$

Let b_{hi} be the proportion of households in the selected cluster compared to the total number of households in EA i in stratum h if the EA is segmented, otherwise $b_{hi} = 1$. Then the probability of selecting cluster i in the sample is:

$$P_{1hi} = \frac{a_h M_{hi}}{\sum M_{hi}} \times b_{hi}$$

Let L_{hi} be the number of households listed in the household listing operation in cluster i in stratum h, let g_{hi} be the number of households selected in the cluster. The second stage selection probability for each household in the cluster is calculated as:

$$P_{2hi} = \frac{g_{hi}}{L_{hi}}$$

The overall selection probability of each household in cluster i of stratum h is therefore the production of the two stages selection probabilities:

$$P_{hi} = P_{1hi} \times P_{2hi}$$

The sampling weight for each household in cluster i of stratum h is the inverse of its overall selection probability:

$$W_{hi} = 1/P_{hi}$$

The differences of the household sampling weight and the individual sampling weights are introduced by individual non-response. The final sampling weights were normalized to give the total number of unweighted cases equal to the total number of weighted cases at the national level, for both household weight and individual weight, respectively. The normalized weights are relative weights that are valid for estimating means, proportions, and ratios, but not valid for estimating the population totals and for pooled data. Let 0ʅ ج ﺟ ﺠ ج be the selection probability of a member from all the eligible members in HH Ê of PSU É of stratum È. The design weight for individual Ë (women or men) from household Ê is given by:

Äج ﺟ ﺠ سج ρ / 0ه ج0ﺟ ج0ʅﺟﺠجﺟ ﺠ ج σ8φ

If only one individual is selected per HH, the selection probability is

0ʅ ج ﺟ ﺠ سج ρ / Π Ï ÆÅ Ì É ÇÍ ÉÅÂÍ ÌÂÅÅÉÒ̂ (Ó (Ê σ8χ

The design weights are the inverse of the ele selection probabilities the chance the unit was selected in the sample. If we have a perfect frame (no frame deficiencies) and full response (no nonresponse), the design weight is also the final survey weight otherwise, we used adjustment by nonresponse. Individual sampling weights are calculated based on HH sampling weight with correction for individual or women nonresponse:

7پ جﺟس 7ﭘ جﺟ / 2پ ج س Äج ﺟ ﺠ z ρ / 2ﭘ ج z ρ / 2پ ج σ8ψ

Where 7ﭘ جﺟ the adjusted design weight for HH nonresponse: 7ﭘ جﺟ س ﻗﺌ ﺠ ﺌ / ﺌﺖ س ه / ﻨ و ﺌ ﻨﺌﺠ ﺌ ﺠﻬﺌ

2ج Is the HH response rate in stratum È d 2ج س Bﺠﺌﺠﺌ ﻗﺌﺠ z ﺌﺠ ﺌﺢ / Bﺠﺌﺠﺌ ﻗﺌﺠ ﺌﺠ ﺌﺢ

Îج ﺟ z Á Î Äج ﺟ ῢ ì the number of HHs found and completed in cluster É of stratum È, respectively.

Where 2پ ج is the individual response rate in stratum È 2پ جس Bﺠﺌ ﺳﭙ ﺠ z ﮈ ﺌ ﺋب ﺌﺠ / Bﺠﺌ ﺳﭙ ﺠ ﮈ ﺋب ﺌﺠ

Where)ج ﺟ z and)ج ﺟ are the number of individuals found and completed in cluster É of stratum È, respectively.

3.3.2. Statistical Models

In this study, the variable of interest is a count variable. When the response or dependent variable (Desired number of children by a woman) is a count which can take on non-negative integer values (0, 1, 2 ...), it is appropriate to use non-linear models based on non-normal distribution to describe the relationship between the dependent variable and a set of predictor variables. For count data, the standard framework for explaining the relationship between the outcome variable and a set of explanatory variables includes the Poisson and Negative Binomial regression models (Gardner, Mulvey, & Shaw, 1995). Unlike linear regression, count data regression models have counts as the response variable that can take only nonnegative integer values. Poisson distribution is the most common probability model for discrete data with observations assumed to have a constant rate of occurrence amongst individual units with the property of equal mean and variance. However, in many applications the variance is greater than the mean and over-dispersion is said to be present. The application of the Poisson distribution to data exhibiting over-dispersion can lead to incorrect inferences and/or inefficient analyses. The most commonly used extension of the Poisson distribution is the negative binomial distribution which allows for unequal mean and variance but may still be inadequate to model datasets with long tails and/or value-inflation (Ayati & Abbasi, 2014; Kassahun, Neyens, Faes, Molenberghs, & Verbeke, 2014; Loquiha, Hens, Chavane, Temmerman, & Aerts, 2013; Sileshi, 2008)

Even though there are several statistical models, some models may not be appropriate to deal with some specific types of data. Their use is solely depending on the types and nature of the data (Karazsia & Van Dulmen, 2008; Long & Freese, 2006). In this study, the form of response variable is a count data, which is most often characterized as non-normal distribution. Thus, to deal with the data and methodological issues related with modeling the desired number of childrenôs, a wide variety of statistical met

which had been developed to analyze data with count response variables. In this study, count regression models such as Poisson and negative binomial were applied. Further multilevel count regression models like multilevel Poisson and multilevel Negative Binomial were used to check the variation among the groups.

3.3.2.1 Single Level Count Regression Models

3.3.2.1.1 Poisson Regression Model

The Poisson distribution is the most common probability distribution for count data. The Poisson probability model is appropriate for events that occur randomly over time and/or space (Dobson & Barnett, 2008).The probability function for Y is given by

0 Ò9 سي Ù Éȶئهِ سي Å۹ڭئج ȶڌئج / ÙِȦ ȟ ȶجيِ π σ8ః

where $y_i = 0, 1, 2, \ldots$ are discrete counts and μ_i is the mean of the Poisson distribution. The mean and variance of Poisson distribution is given as

$$E(y_i) = Var(y_i) = \mu_i$$

This property of the Poisson distribution is known as equi-dispersion.

One specification that is mostly used for the mean parameter μ_i is the exponential specification. This specification ensures that μ_i is non-negative and it is given as

$$E(y_i) = \mu_i = \exp(x_i'\beta) \qquad 3.0$$

where $x_i = (1, x_{1i}, x_{2i}, \ldots, x_{ki})'$ is a vector of explanatory varia

column vector of unknown parameters to be estimated. The estimation is undertaken by using maximum likelihood method. The likelihood function of the Poisson model based on a sample of n independent observations is given by

$$L(\beta; y_i) = \prod_{i=1}^{n} \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!} \qquad 3.1$$

The log-likelihood function is

$$l = \ln L(\beta; y_i) = \sum_{i=1}^{n} \left[y_i \ln(\mu_i) - \mu_i - \ln(y_i!) \right] \qquad 3.2$$

The likelihood equation for estimating the parameter is obtained by taking the partial derivations of the log-likelihood function and setting them equal to zero.

If $E(y_i) < Var(y_i)$, then we speak about over- dispersion, and when $E(y_i) > Var(y_i)$ we say we have under-dispersion. Next, we employed two tests of over dispersion where the Null Hypothesis (H_0) is: mean and variance of the response variable are equal against the Alternative Hypothesis (H_1): variance exceeds the mean. There are two basic criteria commonly used to check the presence of over dispersion:

1. Deviance,

$$D = 2\sum_{i=1}^{n} \left\{ y_i \ln\left(\frac{y_i}{\hat{\mu}_i}\right) - (y_i - \hat{\mu}_i) \right\} \qquad 3.3$$

Where, y is the number of events, n is the number of observations and $\hat{\mu}_i$ is the fitted Poisson mean.

2. Pearson chi-square test, χ^2 is also given by

$$\chi^2 = \sum_{i=1}^{n} \frac{(y_i - \hat{\mu}_i)^2}{\hat{\mu}_i} \qquad [illegible]$$

If the model fits the data, both deviance and Pearson Chi-square statistics divided by the degrees of freedom are approximately equal to one. Values greater than one indicate the data is an over dispersed, while values smaller than one indicate an under-dispersion. It is possible to account for over-dispersion with respect to the Poisson model by introducing a scale (dispersion) parameter into the relationship between the variance and the mean (Pedan, 2001). Another way of checking the presence of over-dispersion is a statistical test of the hypothesis: [illegible] If P-value of LRT < (level of significance), [illegible]-dispersion and the Negative Binomial model is preferred.

3.3.2.1.2 Negative Binomial Regression Model

The negative binomial model is an extension of the Poisson model to overcome possible over dispersion in the data (Lord & Mannering, 2010) caused by heterogeneity or an excess number of zeros (or both) to some degree is inherent to most Poisson data. If a Poisson regression model doesn't fit the data and [illegible] increasing faster than the model allows (i.e. if a plot of the residuals versus linear predictors appears to fan out), then a simple scale-factor adjustment is not appropriate. One way to handle this situation is to fit a parametric model that is more dispersed than the Poisson. A natural choice is the negative binomial (MacDonald & Lattimore, 2010).

This study used the likelihood ratio test to determine the more appropriate model between the Poisson Regression and Negative Binomial Regression. (Hilbe, 2011) used Negative Binomial Regression to Model over dispersed Poisson data. The Negative Binomial Regression Model uses a log link function between the dependent variable and independent variables.

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. The NB regression model is

$$P(Y_i=y_i)=\frac{\Gamma\left(y_i+\frac{1}{\alpha}\right)}{y_i!\,\Gamma\left(\frac{1}{\alpha}\right)}\left(1+\alpha\mu_i\right)^{-\frac{1}{\alpha}}\left(1+\frac{1}{\alpha\mu_i}\right)^{-y_i};\quad y_i=0,1,2,\ldots \tag{2.4}$$

with mean and variance are given by

$$E(Y_i)=\mu_i=\exp(x_i\beta)\ \text{and}\ Var(Y_i)=\mu_i(1+\alpha\mu_i) \tag{2.5}$$

where α shows the level of over-dispersion and it is constant and $\Gamma(.)$ is the gamma function. If $\alpha=0$, NB Regression Model will reduce to Poisson Regression Model. Often data will show over-dispersion (Variance > mean) or under-dispersion (Variance < mean). With over-dispersed data we may well use the Negative Binomial Regression model. We relate parameters μ_i to covariates $x_i\in R^p$ through the log-link function so that

$$E(Y_i)=\mu_i=\exp(x_i'\beta) \tag{2.6}$$

where, x_i' is $1\times p$ row vector of covariate (including an intercepts), p is the number of covariate in the model and column vector of unknown regression parameters. The likelihood function of the NB model based on a sample of n independent observations is given by

$$L(\mu,\alpha;y_i)=\prod_{i=1}^{n}\frac{\Gamma\left(y_i+\frac{1}{\alpha}\right)}{y_i!\,\Gamma\left(\frac{1}{\alpha}\right)}\left(1+\alpha\mu_i\right)^{-\frac{1}{\alpha}}\left(1+\frac{1}{\alpha\mu_i}\right)^{-y_i} \tag{2.7}$$

The log-likelihood function l of NB regression model is

$$l=\sum_{i=1}^{n}-\ln(y_i!)+\sum_{i=1}^{n}\left[\alpha y_i-\alpha j+1-\left(y_i+\frac{1}{\alpha}\right)\ln(1+\alpha\mu_i)+y_i\ln(\mu_i)\right] \tag{2.8}$$

The likelihood equations for estimating μ_i and α are obtained by taking the partial derivations of the log-likelihood function and setting them equal to zero.

3.3.2.2 Multilevel Count Regression Models

The basic idea of multilevel analysis is that data sets with a nesting structure that includes unexplained variability at each level of nesting are usually not adequately represented by single level regression. The reason is that the unexplained variability in single-level regression analysis is only the variance of the residual term. Variability in multilevel data, however, has a more complicated structure related to the fact that several populations are involved in modeling such data: one population for each level. Explaining variability in a multilevel structure can be achieved by explaining variability between level-1 units but also by explaining variability between higher-level units (Hox, Moerbeek, & van de Schoot, 2010).

Multilevel analysis is a methodology for the analysis of data with complex patterns of variability, with a focus on nested sources of variability. These are used when the data structure is hierarchical with elementary units at level 1 nested in clusters at level 2, which in turn may be nested in (super) clusters at level 3, and so on. The latent variables, or random effects, are interpreted as unobserved heterogeneity at the different levels which induce dependence among all lower-level units belonging to a higher-level unit. Random intercepts represent heterogeneity between clusters in the overall response and random coefficients represent heterogeneity in the relationship between the response and explanatory variables.

The best approach to the analysis of multilevel data is an approach that represents within-group as well as between-group relations within a single analy the higher levels of the nesting hierarchy (Hox et al., 2010). In the case of this study the individuals are nested in regions so two-level count regression model is a good way to go. The women are level-1 and the regions are level-2.The following is the necessary notation to specify the multilevel regression model in this study.

Let Ùج ج represent the measure of the response variable Ùfor individual Éat group Ê8ndex Êسي ρĥςĥ8 ĥ. denotes higher level units (groups) and index Éسي ρĥςĥ8 8ĥ. جdenotes the measures of individuals at group j. Let 8ج ج Đسي ρĥςĥ8 ĥ0, denotes the 0 covariates included in the analysis, as measured at children Ébelonging to group Ê ɼي جis assumed to vary randomly and given by the sum of an average intercept ɼيand group dependent deviations 5ي ج(assumed mutually independent and normally distributed with mean zero and variance ʎي), that is, ɼيطى Bج ɼج 8ج ج Đسي ρĥςĥ8 ĥ0ĥdenotes slope coefficients and ʀج جis a residual term, assumed tohave mean zero and variance ʎ. Then we may have the following types of models:

3.3.2.2.1 Testing heterogeneous proportions

For the proper application of multilevel analysis, the first logical step is to test heterogeneity of proportions between groups. The most commonly used test statistic to check for heterogeneity of proportions between groups is the chi-square. To test whether there are indeed systematic differences between the groups, the well-known chi-square test can be used. The test statistic of the chi-squared test for contingency table is often given in familiar form:

$$\chi^2 = \sum \frac{(O-E)^2}{E} \qquad (3.1)$$

where O is the observed and E is the expected counts in the cell of contingency table. It can also be written as:

$$\chi^2 = \sum_{j=1}^{N} n_j \frac{(\hat{p}_j - \hat{p})^2}{\hat{p}(1-\hat{p})} \qquad (3.2)$$

where $\hat{p}_j = \frac{1}{n_j}\sum_{i=1}^{n_j} Y_{ij}$ is the proportion of women in region j,

$\hat{p} = \frac{1}{M}\sum_{j=1}^{N}\sum_{i=1}^{n_j} Y_{ij}$, the overall proportion of women with $M = \sum_{j=1}^{N} n_j$.

This statistic χ^2 chi-square statistic follows approximately central chi-square distribution with $N-1$ degrees of freedom.

Estimation of between and within-groups variance: the theoretical variance between the group dependent probabilities, i.e., the population value of $var(p_j)$ can be estimated by:

$$\hat{\tau}^2 = S^2_{between} - \frac{S^2_{within}}{\tilde{n}} \qquad (3.3)$$

where $\tilde{n} = \frac{1}{N-1}\left(M - \frac{\sum n_j^2}{M}\right)$ between-groups $S^2_{between} = \frac{1}{\tilde{n}(N-1)}\sum_{j=1}^{N} n_j(\hat{p}_j - \hat{p})^2$ and Within-groups variance: $S^2_{within} = \frac{1}{M-N}\sum_{j=1}^{N} n_j \hat{p}_j(1-\hat{p}_j)$

3.3.2.2.2 Random Intercept-only Model

This is the simplest case of hierarchical linear model in which there are no explanatory variables at all. This model only contains random groups and random variation within groups. It can be expressed as a model where the dependent variable is the sum of a general mean, γ_{0} a random effect at the group level, U_{0j}, and a random effect at individual level, R_{ij}. That is,

$$Y_{ij} = \gamma_{0} + R_{ij} = \gamma_{0} + U_{0j} + R_{ij} \qquad (3.4)$$

This model is useful because it gives us an estimate of intra-group correlation.

$$\rho = Corr(Y_{ij}, Y_{i'j}) = \frac{\sigma_u^2}{\sigma_u^2+\sigma_e^2}, \quad i \neq i' \qquad (3.2)$$

which is referred to as intra-group correlation.

For intercept-only model $E(Y_{ij}) = \gamma_0$ and $Var(Y_{ij}) = Var(u_j) + Var(e_{ij}) = \sigma_u^2 + \sigma_e^2$

$Cov(Y_{ij}, Y_{i'j}) = Var(u_j) = \sigma_u^2$ (The covariance between two individuals $(i \neq i')$ in the same group j). This correlation measures the proportion of the total variance which is between-groups. The intercept-only model also gives us the value of the deviance, which is a measure of the degree of miss-fit of the model (H. Goldstein, 2011).

3.3.2.2.3 Random Intercept Model

This is a model in which all lower level explanatory variables are fixed. This means that the corresponding variance components of the slope are fixed at zero. It is used to assess the contribution of each individual explanatory variable.

$$Y_{ij} = \gamma_0 + \sum_{h=1}^{p} \gamma_h X_{hij} + U_{0j} + R_{ij} \qquad (3.3)$$

Note that the first part $\gamma_0 + \sum_{h=1}^{p} \gamma_h X_{hij}$ is the fixed part of the model, because the coefficients arefixed. The remaining part $U_{0j} + R_{ij}$ is called the random part of the model.

3.3.2.2.4 Random intercept and slope model

This is used to assess whether the slope of any of the explanatory variables has a significant variance component between the groups.

$$Y_{ij} = \gamma_0 + \sum_{h=1}^{r} \gamma_h X_{hij} + U_{0j} + \sum_{h=1}^{p} U_{hj} X_{hij} + R_{ij} \qquad (3.4)$$

The first part, $\gamma_0 + \sum_{h=1}^{p} \gamma_h X_{hij}$ is called the fixed part of the model and the second part, $U_{0j} + \sum_{h=1}^{p} U_{hj} X_{hij} + R_{ij}$, is called the random part. The term $\sum_{h=1}^{p} U_{hj} X_{hij}$ can be regarded as arandom interaction between group and the explanatory variables.

This model implies that the groups are characterized by two random effects: their intercept and their slopes. It assumes that, for different groups, the pairs of random effects $(U_{0j}, U_{hj}, \ldots$

ρȟ;8Ɖ are independent and identically distributed, that they are independent of the level-1 residuals, ʀ, and that all ʀ are independent and identically distributed.

3.3.2.3 Multilevel Poisson Regression Model

The multilevel Poisson model can be further extended by including a varying exposure rate Í. The multilevel Poisson regression model for a count Ù for É individual in the Ê group is expressed as follows (Hox et al., 2010).

Ù 0 Ï É Ó Ő ȟ Î

The link function for maximum likelihood Poisson distribution is given as;

Ì ÏȻ Ș Ẋ È ÅȊȘÅ ɼ ɼ 8 ɼ. 8. Ẽ ɼ 8 σ&; χ

Letting ɼ ɼ 5 and ɼ ɼ 5

From (3.27)

Ì ÏȻ ɼ ɼ8 5 ɼ8 σ&; ψ

The first part of equation (3.28) ɼ B ɼ8 is called the fixed part of the model. The second part 5 B ɼ8 is called the random part. The groups are characterized by Ë ρ random coefficients 5ȟ5 ȟ5. ȟ8 ȟ5. The random coefficients are independent between groups, but may be correlated within groups. It is assumed that the vectors 5ȟ5 ȟ5. ȟ8 ȟ5 is distributed with means zero and has a multivariate normal distribution with a constant variance matrix. The variances an

are

Ö ÁÒȹ ʎ ʎ Ã ÏȹȟȽ ʎ ÈȟÐ πȟρȟ;ȟ8 ȟË Æ ÏÉÒ È σ&; ω

3.3.2.4 Multilevel Negative Binomial Regression Model

The multilevel negative binomial regression model for a count Ù for É individual in the Ê group is expressed as follows (Hox et al., 2010).

Multilevel negative binomial regression model is given by;

[illegible]

with mean and variance given, respectively, as follows:

[illegible]

where [illegible]

3.4 Maximum likelihood estimation of the parameters

The method used to estimate the regression coefficients of Poisson, negative binomial, ZIP or ZINB models, is the maximum likelihood estimation (MLE). Statistical software finds model parameter estimates using a numerical iterative algorithm. The most common iterative algorithms are the Newton-Rapson algorithm and Fisher information matrix. The algorithm starts at an initial guess for the parameter values that maximize the likelihood function. The Fisher scoring algorithm for doing this was first proposed by R. A. Fisher. The dispersion parameter [illegible] may be estimated by maximum likelihood or method of moments. Maximum likelihood estimation involves iterative solution of the equation, [illegible] which is different for each response distribution (De Jong & Heller, 2008).

3.5 Assessing Model Adequacy

Assume that estimation is by the method of maximum likelihood. Tests for the validity for the null hypothesis can be based on any one of the following three principles:

3.5.1 Wald Test

Wald test is used to test statistical signif

statistic is chi-square statistic which desirable outcome of non-significantly, indicating that the model predication does not significantly differ from the observed.

The Hypothesis to be test: ([illegible] then with non-null standard error of [illegible] at [illegible] level

significance.

The Wald test statistics for this hypothesis is [illegible] has an approximate standard normal distribution. Equivalently, [illegible] has approximately a chi-squared distribution with DF = 1. This type of statistic, which uses the standard error evaluated at the ML estimate, is called a Wald statistic. The Wald statistic is

$$Z^2 = \left(\frac{\hat{\beta} - \beta_0}{SE(\hat{\beta})}\right)^2$$

Under H_0 true Z^2 is a chi-square distribution with 1 degree of freedom. Wald statistics are for small samples. Likelihood-ratio tests are generally considered to be superior (Agresti, 2007).

3.5.2 Likelihood Ratio Test

For nested models, the LRT is a test of a null hypothesis (H_0) against an alternative (H_1) based on the ratio of two log-likelihood functions. The likelihood ratio test is a test of the overall model. The overall test statistic for likelihood ratio test is given as(Lawless, 1987): Likelihood ratio test

$$G^2 = -2(l_0 - l_1) \sim \chi^2_{(p-1)}$$

where l_0 is the log-likelihood of the null model and l_1 is the log-likelihood of the full model. This statistic is called the likelihood-ratio test statistic.

Comprising k predictor, p is number of parameters and $\chi^2_{(p-1)}$ is a chi-square distribution with p-1 degree of freedom. If the test statistics exceeds the critical value, the null hypothesis is rejected. That means the overall model is significant.

3.5.3 Information Criteria

AIC and BIC are goodness of fit criteria used for selection of non-nested models. The likelihood ratio test was used to compare the Poisson model and NB model. Many Monte-Carlo simulations indicate that the BIC and AIC selection criteria need to be used together (Wang & Famoye, 1997). The model with smallest value of AIC or of BIC is preferable. Selecting an appropriate model is often based on a standard likelihood information criteria, for example, Akaike information criteria (Akaike, 1973) or Bayesians information criteria (Raftery, 1986) abbreviated by AIC and BIC, respectively, Where

$$AIC = -2\log L + 2k \quad \text{and} \quad BIC = -2\log L + k\ln(n)$$

where, k = number of parameters and n = number of observations

CHAPTER FOUR

RESULT AND DISCUSSION

The statistical analyses were performed using South Texas Art Therapy Association (STATA) version 14, Statistical Package for Social Science (SPSS) version 23, R version 3.4.4 and Microsoft-Excel.

4.1 Descriptive Statistics

Before performing any advanced statistical analysis, it is better to examine the overall picture of the desired number of children of an Ethiopian women at reproductive age (15-49), all descriptive analysis were performed using weighted data.

Table 4.1. Descriptive statistics of DNC using weighted & unweighted Data

Variable	**Category**	**Mean**	**Std.Dev.**
Desired number of children (DNC)	Data is weighted	4.5	2.77
	Data is unweighted	5.04	3.33

Table 4.1 shows that mean and standard deviation of desired number of children by an Ethiopian woman at the reproductive age are lower for the weighted dataset than for the unweighted dataset (4.5 versus 5.04 children per women respectively). Using the weighted data also reduce bias, standard error, sampling error. Descriptive analysis of data based on weights provide more precise results than that of the unweighted survey data result (Kish, 1995)

The variance of the outcome variable (desired number of children), 7.63, is greater than the population mean, 4.50 and the ratio $\frac{۵8۴}{۲8۳}$ ۱ سي ρ8φ ωحي ρthe results suggesting over dispersion.

As shown in Figure 4.1, the distribution of the desired number of children has a somewhat slowly decreasing tail and this leads to have a positively skewed (or right tailed) distribution. The minimum desired number of children per women is 0 (zero) and the maximum is 30 of the weighed data.

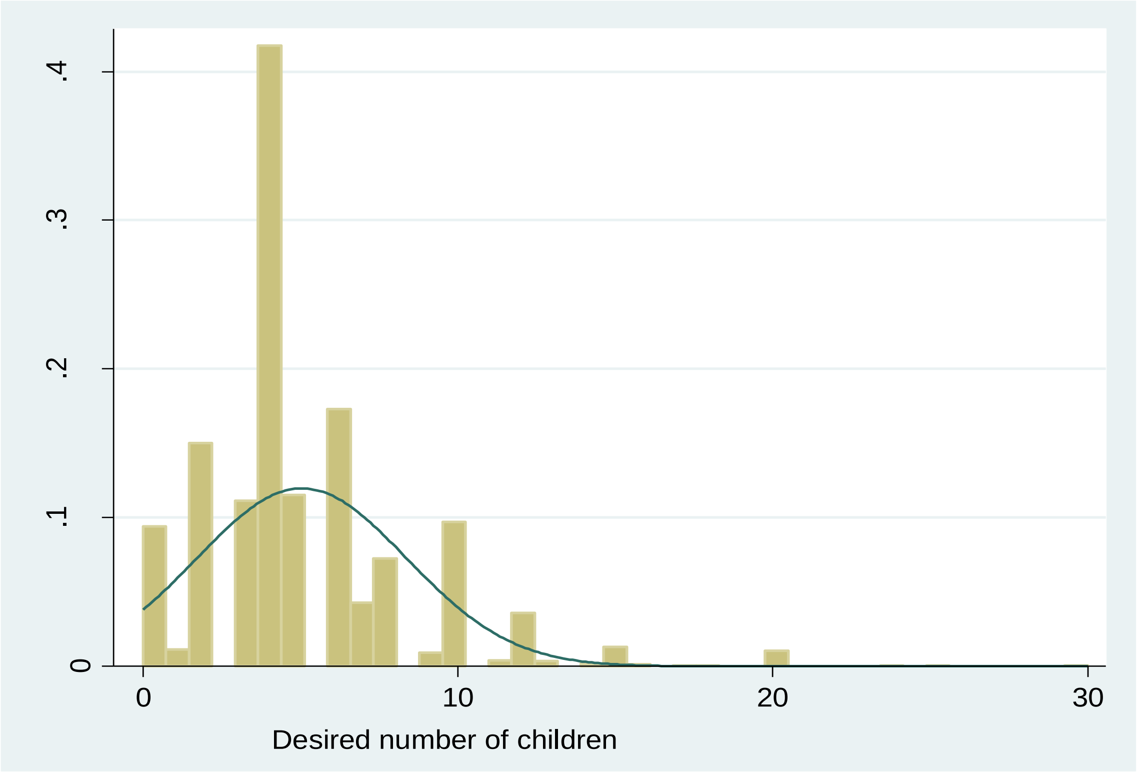

Figure 4.1. Histogram for desired number of children by women weighted data

Summary Statistics of some selected variables for the desired number of children **(**DNC**)** by women aged 15-49 years are presented in Table 4.2.

Table 4.2. Mean and Standard deviation of desired number of children among women aged 15-49 and proportion of women in each category of the explanatory variables.

Variable	Category	Mean	Std. Dev.	Obs.	Proportion
Total desired children		**4.4522**	**2.7617**	**13941**	
Womenôs age	15-19	3.5773	2.3404	3247	0.2276
	20-24	3.9133	2.2409	2676	0.1849
	25-29	4.3906	2.5079	2537	0.1895
	30-34	4.7751	2.7219	1950	0.1445
	35-39	5.2986	3.0908	1655	0.1190
	40-44	5.6694	3.3033	1070	0.0759
	45-49	5.6586	3.4606	806	0.0586
Household head	Male	4.5072	2.7489	9651	0.7624
	Female	4.2754	2.7953	4290	0.2376
Living children	No living child	3.5622	2.1931	5166	0.3502
	Living child	4.9318	2.9136	8775	0.6498
Contraception using	Not Using	4.5037	2.9526	10883	0.7421
	Using	4.3038	2.1120	3058	0.2579
Region	Tigray	4.7507	2.0434	1436	0.0690
	Afar	5.6438	4.5948	888	0.0073
	Amhara	4.0095	2.0862	1511	0.2341
	Oromia	4.0896	2.9230	1684	0.3609
	Somali	10.588	4.5234	1093	0.0249
	Benshangul G.	5.0117	2.4966	1012	0.0103
	SNNPE	4.9074	2.1874	1712	0.2171
	Gambela	4.5457	2.4039	974	0.0030
	Harari	4.1531	2.5537	816	0.0025
	Addis Ababa	3.5605	1.8653	1786	0.0650
	Dire Dawa	5.4076	3.0950	1029	0.0059
Place of Residence	Urban	3.8355	2.1813	5012	0.2340
	Rural	4.6405	2.8901	8929	0.7659
Wealth index	Poorest	5.4981	3.6838	3189	0.1560
	Poorer	4.5986	2.7714	1787	0.1758
	Middle	4.4675	2.6316	1790	0.1907
	Richer	4.2784	2.5059	1825	0.1983
	Richest	3.8884	2.1806	5350	0.2792
Womenôs Employm	Not working	4.5407	2.8509	8813	0.6634
	Working	4.2775	2.5681	5128	0.3366
Womenôs educati	No Education	5.2122	3.2140	5827	0.4502
	Primary	3.9511	2.3035	4801	0.3636
	Secondary	3.5728	1.7326	2151	0.1247
	Higher	3.6325	1.7327	1162	0.0614
Religion	Orthodox	3.9859	2.1003	5855	0.4354
	Catholic	3.5901	2.3280	86	0.0076
	Protestant	4.5038	2.3522	2631	0.2443
	Muslim	5.0592	3.5976	5229	0.3004
	Traditional	5.1134	4.2838	75	0.0068
	Other	6.2882	3.6188	65	0.0055
Marital status	Single	3.4713	2.1606	4015	0.2744
	Married	4.9429	2.8921	8321	0.6225
	Separated	4.0999	2.6311	1605	0.1031
Husbandôs Educa	No Education	5.3003	3.2212	3659	0.2802
	Primary	4.8487	2.6150	2702	0.2384
	Secondary	4.2242	2.3257	1127	0.0644
	Higher	4.1304	2.2552	965	0.0484
	Donôt kno	4.0862	3.2913	75	0.0041
Husbandôs Emplo	Not working	5.7651	3.5617	837	0.0468
	Working	4.8596	2.8082	7569	0.5820
	Donôt kno	4.7322	3.0661	122	0.0067

Age of women: Among the seven age groups of women the average number of children per women is high (5.66) among the oldest age group (40-44) and small (3.57) in the youngest age group (15-19). Suggesting that average desired number of children is positively correlated with age i.e., the older the respondent, the more children that she considers. Out of a total of 13941 women in the weighted data, 22.7 percent of the women were in the age group 15-19, 18.4 percent in 20-24, 18.9 percent were in 21-25, 14.4 percent were in between age 30-34, and the rest 48.3percent were in between age 35-49 age groups.

Sex of household head: The average desired number of children per women nearly the same whether the household head was male or female. The desired number of children when the household head was male and female was 4.50 and 4.27 respectively. The largest percent of household headship was in male (76%) and the

Living child: From Table 4.2 above we see that women without living children exhibited lower average desired number of children (3.56) than the average desired number of children by women having living children (4.93).

Contraception Use: The desired number of children among users and non-users of contraceptive were 4.30 and 4.50 respectively.

Region and Place of residence: The mean desired number of children per women was high in rural (4.64) areas as compared to urban areas (3.83).The highest average desired number of children was recorded in Somali region (10.58) and the lowest in Addis Ababa city administration (3.56)

Wealth index: Table 4.2 also displays that women in the poorest economic level, and woman having no work have highest desired number of children as compared to relatively well-to-do and working women respectively. It also displays a decreasing trend in mean number of children for an increasing level of education of mothers

4.2. Single Level Analysis

4. 2.1. Parameter Estimation

Table 4.3. The results of over-dispersion test after fitting a Poisson regression

Statistics	**Value**	**Degrees of freedom**	**Value/Deg. Freedom**	**P-value**
Deviance test statistics	20712.96	13925	1.4874	0.0000
Pearson Chi-square statistic	16592.95	13925	1.1915	0.0000

The ratio of the Deviance and Pearson Chi-square statistic to their corresponding degrees of freedom are greater than one, indicating over dispersion in the data and the over dispersion regression model is preferred over the Poisson model. The fact that the Negative Binomial regression model is favored over the Poisson regression model has also been confirmed by the likelihood-ratio test. Since the value of this statistic is 5478.47 with Ðحى π8π π ,πwφe reject the null hypothesis that there is equi-dispersion and conclude that there is significant over-dispersion in the data.

When the assumption of the equality of the variance and the mean in the Poisson regression model is violated, over-dispersion occurs and the standard error estimates will be biased which leads to incorrect value of the test statistic. Consequently, the covariates may be wrongly interpreted (Yaacob, Lazim, & Wah, 2010).

Figure 4.2: The Observed and predicted probabilities of desired number of children

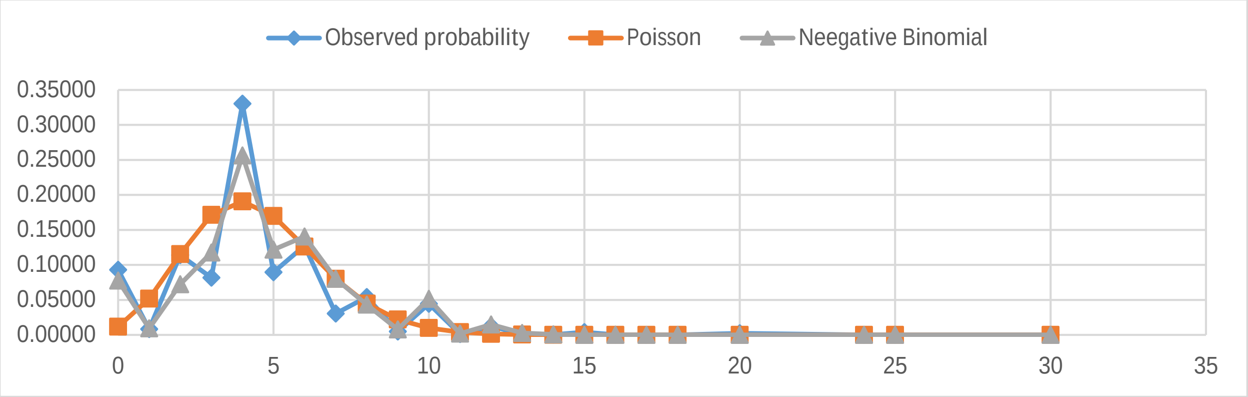

Table 4.4. Observed and predicted probabilities of desired number of children

Probability				
Count	**Obs.**	**Observed prob.**	**Poisson**	**Negative Binomial**
0	958	0.09291	0.01165	0.07763
1	116	0.00827	0.05188	0.00937
2	1,532	0.11390	0.11550	0.07246
3	1,134	0.08170	0.17140	0.11775
4	4,257	0.33019	0.19078	0.25644
5	1,177	0.08942	0.16987	0.12188
6	1,765	0.12753	0.12605	0.14061
7	436	0.03061	0.08017	0.08005
8	740	0.05398	0.04462	0.04328
9	94	0.00488	0.02207	0.00778
10	993	0.04441	0.00983	0.05159
11	41	0.00131	0.00398	0.00198
12	366	0.01212	0.00148	0.01498
13	36	0.00110	0.00051	0.00286
14	19	0.00057	0.00016	0.00084
15	135	0.00404	0.00005	0.00013
16	16	0.00036	0.00001	0.00012
17	2	0.00003	0.00000	0.00001
18	6	0.00015	0.00000	0.00002
20	105	0.00234	0.00000	0.00016
24	2	0.00002	0.00000	0.00004
25	5	0.00005	0.00000	0.00003
30	6	0.00013	0.00000	0.00000

From Figure 4.2 above the plots of the differences between predicted and observed values from each model against the observed value of the response was used to visualize how the model adequately expresses the response variable. And the predicted probabilities for Negative Binomial model were closest to the observed probabilities. Therefore the Negative Binomial model is the preferred model than the Poisson model.

Table 4.4 presents the values for observed and predicted probabilities for each model. It indicated that, the values are very close to the observed values for Negative Binomial regression model in predicting each count desired children per mother.

4.2.2. Negative Binomial model fit results

Based on the above mentioned criteria for model selection and evaluation, Negative Binomial regression model was best for fitting the desired number of children by women.

Table .4.5. The estimated Negative Binomial model for desired number of children.

						[95% CI for IRR]	
Parameter	**Coef.**	**Std. Err.**	**Z**	**P>|z|**	**IRR**	**Lower**	**Upper**
Region (Ref. Tigray)							
Afar	-0.0160369	0.0526778	-0.30	0.761	0.984091	0.8875562	1.091125
Amhara	-0.2069374	0.0197499	-10.48	0.000	0.8130705	0.7821986	0.8451609
Oromia	-0.2844062	0.020818	-13.66	0.000	0.7524609	0.7223766	0.7837982
Somali	0.5822502	0.0304219	19.14	0.000	1.790062	1.686448	1.900042
Benshangul G.	-0.0582826	0.0462519	-1.26	0.208	0.9433833	0.8616255	1.032899
SNNPE	-0.0743472	0.0225847	-3.29	0.001	0.9283493	0.8881519	0.970366
Gambela	-0.101362	0.0844782	-1.20	0.230	0.9036059	0.7657219	1.066319
Harari	-0.2081515	0.0952826	-2.18	0.029	0.812084	0.6737461	0.9788265
Addis Abeba	-0.1842444	0.027863	-6.61	0.000	0.8317325	0.7875292	0.8784169
Dire Dawa	0.0681426	0.0581295	1.17	0.241	1.070518	0.9552434	1.199703
Womenôs Age (Ref. 15-19)							
20-24	0.0117392	0.0175254	0.67	0.503	1.011808	0.9776437	1.047167
25-29	0.0736425	0.0193842	3.80	0.000	1.076422	1.036293	1.118105
30-34	0.1108057	0.0212121	5.22	0.000	1.117178	1.071684	1.164603
35-39	0.2079056	0.0218454	9.52	0.000	1.231097	1.179499	1.284953
40-44	0.262217	0.0236552	11.08	0.000	1.299809	1.240921	1.361491
45-49	0.2828478	0.0252323	11.21	0.000	1.326903	1.262878	1.394174
Household head (Ref. Male)							
Female	0.0311365	0.0129543	2.40	0.016	1.031626	1.005763	1.058155
Living children (Ref. No)							
Yes	0.0271139	0.0193125	1.40	0.160	1.027485	0.9893195	1.067123
Contraception using (Ref. No)							
Yes	-0.0713473	0.0115455	-6.18	0.000	0.9311384	0.9103045	0.9524491
Place of residence (Ref. urban)							
Rural	0.0500667	0.0195326	2.56	0.010	1.051341	1.011853	1.09237
Wealth index (Ref. poorest)							
Poorer	-0.0283017	0.015611	-1.81	0.070	0.972095	0.9428023	1.002298
Middle	-0.0398167	0.0155976	-2.55	0.011	0.9609655	0.9320326	0.9907966
Richer	-0.0447052	0.0159461	-2.80	0.005	0.9562793	0.9268542	0.9866386
Richest	-0.0178325	0.0206232	-0.86	0.387	0.9823256	0.943411	1.022845
Women employment (Ref. Not employed)							
Working	-0.0043275	0.0103273	-0.42	0.675	0.9956819	0.9757307	1.016041
Womenôs education (**Ref. NO Edu.)**							
Primary	-0.0788832	0.012485	-6.32	0.000	0.9241479	0.9018083	0.9470408
Secondary	-0.0745511	0.0196935	-3.79	0.000	0.9281601	0.8930171	0.9646861
Higher	-0.0333944	0.0269156	-1.24	0.215	0.9671571	0.9174584	1.019548
Religion (Ref. Orthodox)							
Catholic	-0.1085843	0.0576741	-1.88	0.060	0.8971033	0.801217	1.004465
Protestant	0.0825574	0.015522	5.32	0.000	1.086061	1.053518	1.119609
Muslim	0.1274407	0.0136297	9.35	0.000	1.135917	1.105975	1.166671
Traditional	0.1813138	0.0534462	3.39	0.001	1.198791	1.079568	1.331181
Other	0.2815007	0.0551606	5.10	0.000	1.325117	1.189327	1.47641
Marital status (Ref. Single)							
Married	0.1931541	0.0547928	3.53	0.000	1.21307	1.089547	1.350596
Separated	0.1529992	0.0343257	4.46	0.000	1.165324	1.089504	1.246421
Husbandôs education (**Ref. No Edu)**							
Primary	0.0154902	0.0129664	1.19	0.232	1.015611	0.9901256	1.041752
Secondary	-0.0372779	0.0220403	-1.69	0.091	0.9634083	0.922677	1.005938
Higher	-0.0567141	0.0268068	-2.12	0.034	0.9448642	0.8965022	0.9958351
Donôt know	-0.2196759	0.0737516	-2.98	0.003	0.8027789	0.6947339	0.9276271
Husbandôs employment **(Ref. Not employed)**							
Working	0.0076366	0.0204152	0.37	0.708	1.007666	0.968142	1.048803
Donôt know	-0.0038168	0.0583212	-0.07	0.948	0.9961904	0.8885855	1.116826
Family size	0.0174839	0.0021494	8.13	0.000	1.017638	1.01336	1.021934
Age at first marriage	-0.0082282	0.0014126	-5.83	0.000	0.9918056	0.9890635	0.9945552
_cons	1.407571	0.0596235	23.61	0.000	4.086018	3.63537	4.592528
/lnalpha	-2.868281	0.0619397			-2.868281	-2.989681	-2.746882
Alpha	0.0567965	0.003518			0.0567965	0.0503035	0.0641275

Note: Alpha is dispersion parameter.

From the results of incident counts the coefficients of the estimated Negative Binomial regression model, can be interpreted as follows: for a one unit change in the predictor variable, the log of the response variable is expected to change by the value of the regression coefficient (Coef.). In NB model, for every one unit incr number of desired children is expected to increase or decrease by approximately the corresponding coefficient in the column of coefficient (Coef.). In this model the variables whose Ðvalue ى π8π ȟ were considered statistically significant.

In the discussion of the count data results we use incident ratio rate (IRR) to interpret the coefficients directly. (Hilbe, 2011).) 2ﺳ2 Å Ø Ð̃ έ Ὸ Ὢ which is important to explain the change in percentage) 2ﻲ2 ρ of significant predictors. The factors household head, Contraceptive use , Place of residence, Wealth inde Marital status, Husbandôs education, Family s significant predictors of this count outcome. are not statistically significant predictors for the outcome variable.

4.3. Multilevel Analysis

This is basically with the expectation that there would be a difference in the number of desired children from individual womenôs among the re Binomial regression in the previous section also revealed such differences. We did this considering the regional variation of womenôs for the number of desired children. In this study, the dependent variable was the count of desired number of children by women through her life time. We considered two levels: individual mothers (as level-1 units) and Region (as level-2 units) in order to identify significant explanatory variables with the number of desired children.

4.3.1. Test of heterogeneity

It is important to deal with testing of the presence of heterogeneity in the dataset as captured by the count regression models. With respect to model performance of count models to account for the heterogeneity in the dataset, we computed the likelihood ratio test as presented in Table 4.7.

Table 4.6: Likelihood ratio test value for multilevel and ordinal count regression models

Selection criteria	Regression model
	Negative Binomial
LRT	116.7

As shown in Table 4.6, to compare the heterogeneous multilevel Poisson and multilevel NB with their standard counterparts, we obtained LRT statistic of 116.7. The value of LRTô model is larger than the chi- square value ʔ̇٥٩ں و سي5.99, which indicates the existence of heterogeneous random effect models.

4.3.2. Model comparisons and assessment

Table 4.7 provides the values of log likelihood and information criteria for multilevel Negative Binomial regression model for random intercept-only model, for random intercept model and for random intercept and random coefficients models.

Table 4.7: Model comparison of multilevel Negative Binomial model

Selection criteria	Multilevel Negative Binomial Regression Model		
	Random Intercept only model	**Random intercept model**	**Random intercept & coefficients model**
log likelihood	-33352.45	-32246.055	-32333.4
AIC	66710.9	64566.11	64750.8
BIC	66733.53	64845.19	65067.6

From the table 4.7 the result showed the values of log likelihood, AIC and BIC were large for random intercept only model and for random intercept and coefficients model. The LL, AIC, and BIC value for random intercept model were (-32246.055, 64566.11, and 64845.19 respectively), revealed that the model is the most parsimonious. Therefore it suggested that the random intercept multilevel Negative Binomial model can efficiently predict the determinant factors that influence desired number of children by women at reproductive age better than random intercept-only and random intercept and coefficients models can.

4.3.3. Discussion and Interpretation of Random intercept Negative Binomial regression model fit results

Table .4.8. Results of Random Intercept Negative Binomial model for desired number of children.

Parameter	Coef.	Std. Err.	Z	ˈI ى ṩöş	IRR	[95% CI for IRR] Lower	Upper
Womenôs Ag-19) (Ref. 1							
20-24	0.0132747	0.018461	0.72	0.472	1.013363	0.9773521	1.050701
25-29	0.0667253	0.0204436	3.26	0.001	1.069002	1.027015	1.112705
30-34	0.0945112	0.0224048	4.22	0.000	1.099122	1.051901	1.148462
35-39	0.1939074	0.0231183	8.39	0.000	1.213984	1.160205	1.270256
40-44	0.2534015	0.0251108	10.09	0.000	1.2884	1.226525	1.353397
45-49	0.2652772	0.0268138	9.89	0.000	1.303792	1.237042	1.374144
Household head (Ref. Male)							
Female	0.0766677	0.0136964	5.60	0.000	1.079683	1.051085	1.109059
Living children (Ref. No)							
Yes	0.0231238	0.0203587	1.14	0.256	1.023393	0.9833614	1.065055
Contraception using (Ref. No)							
Yes	-0.0845915	0.012204	-6.93	0.000	0.9188875	0.897169	0.9411318
Place of residence (Ref. urban)							
Rural	0.0079402	0.0202275	0.39	0.695	1.007972	0.9687923	1.048736
Wealth index (Ref. poorest)							
Poorer	-0.1407077	0.0162564	-8.66	0.000	0.8687432	0.8414997	0.8968688
Middle	-0.1550731	0.0162146	-9.56	0.000	0.8563526	0.8295656	0.8840045
Richer	-0.1688103	0.0165373	-10.21	0.000	0.8446691	0.8177302	0.8724955
Richest	-0.1530698	0.0216186	-7.08	0.000	0.8580698	0.8224714	0.895209
Women employment (Ref. Not employed)							
Working	-0.010904	0.0109236	-1.00	0.318	0.9891553	0.9682026	1.010561
Womenôs education (**Ref. NO Edu.)**							
Primary	-0.0919283	0.0132575	-6.93	0.000	0.9121705	0.8887738	0.9361831
Secondary	-0.0844236	0.0208422	-4.05	0.000	0.9190418	0.8822555	0.957362
Higher	-0.0644679	0.0284637	-2.26	0.024	0.9375662	0.8866936	0.9913575
Religion (Ref. Orthodox)							
Catholic	-0.0896242	0.060173	-1.49	0.136	0.9142747	0.8125637	1.028717
Protestant	0.1080062	0.012775	8.45	0.000	1.114055	1.086507	1.142301
Muslim	0.1488404	0.0121185	12.28	0.000	1.160488	1.133249	1.188381
Traditional	0.0593275	0.0564141	1.05	0.293	1.061123	.9500486	1.185183
Other	0.2726313	0.0589043	4.63	0.000	1.313416	1.170207	1.47415
Marital status (Ref. Single)							
Married	0.1826926	0.0578365	3.16	0.002	1.200445	1.071795	1.344538
Separated	0.109312	0.0359377	3.04	0.002	1.11551	1.039641	1.196916
Husbandôs educatio							
Primary	0.0069265	0.0137226	0.50	0.614	1.006951	0.9802287	1.034401
Secondary	-0.0241666	0.0233765	-1.03	0.301	0.9761231	0.9324091	1.021887
Higher	-0.0242655	0.0284279	-0.85	0.393	0.9760265	0.9231319	1.031952
Donôt know	-0.1738741	0.0778496	-2.23	0.026	0.8404027	0.7214757	0.9789333
Husbandôs employme **(Not employed)**							
Working	-0.0663931	0.0215762	-3.08	0.002	0.9357629	0.8970159	0.9761837
Donôt know	-0.0945897	0.0620669	-1.52	0.128	0.9097462	0.8055432	1.027429
Family size	0.0199469	0.0022731	8.78	0.000	1.020147	1.015612	1.024702
Age at first marriage	-0.0069415	0.0014893	-4.66	0.000	0.9930825	0.990188	0.9959855
_cons	1.437436	0.0603361	23.82	0.000	4.20989	3.740352	4.738369
/lnalpha	-2.355457	0.0424003	-55.55	0.000	-2.355457	-2.43856	-2.272354
Region							
var(_cons)	0.0083395	0.0075838			0.0083395	0.001403	0.0495692

Note: Alpha is a dispersion parameter. ÐÖ Á Ìى Õπ8t υ

The results from the random intercept model are given in Table 4.8. As can be seen from the table, desired number of children per mother varies among regions. Since the level-two (region level) variance of the random intercept σ^2_{u0} = 0.0083395 was found to be significant, this was an indication that the number of desired children per mother differs among regions. Also from the table we see that the inclusion of level one covariates decreased regional variations from 0.021625 (level-two variance without covariates) to 0.0083395, (see Table 4.8 and Appendix 3 table A.3.1) it indicates that there is a significant variation between regions in desired number of children by women. The results of multilevel negative binomial regression of random intercepts was identified that the predictors Women's age, Wealth Index, Women's education, Religion, Marital status, Family size and Age at first marriage were statistically significant predictors. Husband's work, place of residence, women's work and living children are not statistically significant predictors for the outcome variable.

The parameters of observed variables can be interpreted much the same way as those from the ordinal model. Thus, everything else being equal except slight difference on random effect in the model, allowing it to randomly vary between regions and holding all the other variables in the model constant (by setting the variance of other coefficients zero).

From the fitted model above, the estimated coefficients for all age groups are positive and show that the desire number of children increases with the incremental age of women. The expected desired number of children that women aged 25-29 would like to have in their lifetime was 6.9% (IRR=1.069002) higher than the expected desired number of children that women aged 15-19 would like to have in their lifetime. more over the expected desired number of children that women aged 45-49 was 30.3% (IRR=1.303792) higher than the expected number of desired children that women aged 15-19 would like to have controlling all other variables in the model and random effect at level two. But there was no significant difference in the desired number of children that women would like to have between age 15-19 and 20-24. But this finding was contrary to the result of a study by (Dudgeon & Inhorn, 2004; Greene, 2000). In literature most of the studies report a negative relationship between the expected number of children and age of women. They indicate that younger women have higher likelihood of having higher desired number of children.

The positive and statistically significant coefficient, 0.0766677 suggested that the expected desired number of children being the head of the house hold female was 7.9% (IRR=1.079683) higher than the expected number of desired children for the head of the household was male. And this results are consistent to the results of (Adhikari, 2010). According to (Adhikari, 2010). Being a house hold head for females are more likely to have more children that they expected than when then head house hold was male.

From the fitted model, the coefficient for the contraception using is negative and statistically significant, shows that the expected desired number of children for contraception user women 8.1% (1-IRR=0.0811125) less desired number of children than contraception non-user women. This finding is in agreement with study by (Adhikari, 2010). This observation holds as a women who are using contraceptive are less likely to have their expected children than the non-user women.

The fitted model shows that the estimated coefficient of wealth index was negative and statistically significance. Implying that women in the poorer index are expected to have 86.8% (IRR=0.8687432) less desired number of children than women in the poorest index and women in the richest wealth index are expected to have 85.8% (IRR=0.8580698) less number of children than women in the poorest index. This finding are consistent with other studies (Upadhyay & Karasek, 2012). They indicated that rich households have better access to food and higher cash incomes than poor households, allowing them a quality diet, better access to medical care and more money to spend on essential nonfood items such as schooling, clothing and hygiene products for their children.

The estimated coefficient for womenôs educa
significance. Thus, primary educat 0.9021705) womenôs
fewer desired number of children than the uneducated women. Moreover higher educated womenôs are expected to have 93.7% (IRR=0.9375612) fewer desired number of children than the uneducated women. In literature most of the studies also report a negative relationship between the expected number of children and w (Purbalanta & Aseldewine, 2016). They indicated that education improves the ability of mothers to implement simple health knowledge and facilitates like family planning methods and contraception using. Furthermore, educated women have greater control over health choices and future plan for their children.

The coefficients for the categories of Religion: Protestant, Muslim and Other were positive and statistically significance, implying that the expected desired number of children were 11.4% (IRR=1.114055), 16% (IRR=1.160488) and 31.3% (IRR=1.313416) respectively higher desired number of children than Orthodox women. But there was no significant difference in the desired number of children that women would like to have between Catholic, Traditional and Orthodox women. And this results are similar to the results of (Adhikari, 2010)

The positive and statistically significant coefficients for married women 0.1826926 and separated women 0.109312, suggested that the expected desired number of children for a married women and separated women were 20% (IRR=1.200445) and 11.5% (IRR=1.11551) higher than the expected number of desired children for single women. This finding are consistent with other studies (Matovu, Makumbi, Wanyenze, & Serwadda, 2017). They believed that married womenôs are more likely to have the expected number of children than those who are single and separated women.

The estimated coefficient for family size was positive and statistically significance, implying that when the number of family size increased by 2% (IRR=1.020147) the expected desired number of children is increasing by one children. An inconsistent study by (Puurbalanta & Aselisewine, 2016) showed that women having large family size were more likely to desire for additional children than those who had small family size.

The estimated coefficient for age at first marriage was negative and statistically significance, implying that as age at first marriage increased by one year the expected desired number of children decreased by 0.69% (IRR=0.9930825). In literature most of the studies report a negative relationship between the expected number of children and age of women at first marriage And this findings are consistent to the results of (Adhikari, 2010)

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The study has empirically investigated and identified the determinants of the desired number of children that women at the reproductive age (15-49) would like to have in their lifetime using count regression model. Data from the 2016 Ethiopia Demographic and Health Survey (EDHS) were used for analysis. The use of the sampling weights when fitting models to such survey data has also been considered. In this study, two count regression models were considered. The variance of the desired number of children was larger than its mean, suggesting the possibility of over-dispersion. In addition, the over-dispersion parameter alpha was found to be significantly different from zero in Negative Binomial regression model. Resulting that negative Binomial regression model was found to be the most appropriate and preferred model than the Poisson regression model.

The findings on the single level Negative Binomial regression model showed that Region, Contraception using, Wealth index, Women education, Husband education and Age at the first marriage were negatively influence for the desired number of children by women at reproductive age and predictors like women age, place of residence, religion, marital status, household head and family size were positively influence for the desired number of children by women at reproductive age.

The study showed that when there was heterogeneity across count data, modelling multilevel count regression model with random effects as covariates provides an unbiased and accurate estimates of parameters. The multilevel Negative Binomial regression model analysis identified that a large degree of heterogeneity in desired number of children per mother was different among regions of Ethiopia. This study was often interested in understanding how explanatory variables affect desired number of children among Ethiopian women.

From the result of multilevel Negative Binomial regression model, the Random Intercept model was found to be the most appropriate and preferred model than the Random intercept only model and the Random intercept & Random coefficients model. Variables such as W

Household head, Religion, Marital status and Family size were positively influence for the desired number of children by women at reproductive age and Age at first marriage Contraception using, Wealth Index and Womenôs education were negatively influence for the desired number of children by women at reproductive age.

5.2 Recommendations

Based on the findings that we have obtained, we recommend the following issues:

- The government, concerned institutions and other involved stakeholders should work to reduce high fertility rate by preparing continuous trainings and capacity buildings related family planning to those regions with high rates of desired number of children.
- Desired number of children differentials per mother among regions are significant. This is an indication that desired number of children 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 desired number of children for each region of Ethiopia separately.

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Table 4.8: AIC value of log-logistic AFT and loglogistic gamma shared frailty models

Model	**AIC**
Log-logistic accelerated failure time	**2393.579**
Log-logistic shared gamma frailty	**2125.545**

4.6.1 Interpretation of log -logistic gamma shared frailty model

From log-logistic gamma shared frailty model in table 4.8, controlling for other covariates, the acceleration factor with 95% CI of acceleration factor for women educational level who attend primary, secondary and higher was 1.133 (1.120, 1.146), 1.361 (1.331, 1.392) and 1.575 (1.526, 1.625) respectively. This indicates primary, secondary and higher educated women had extended age at first birth by a factor of 1.133, 1.361 and 1.575 respectively at 5% level of significance as compared with women who were uneducated.

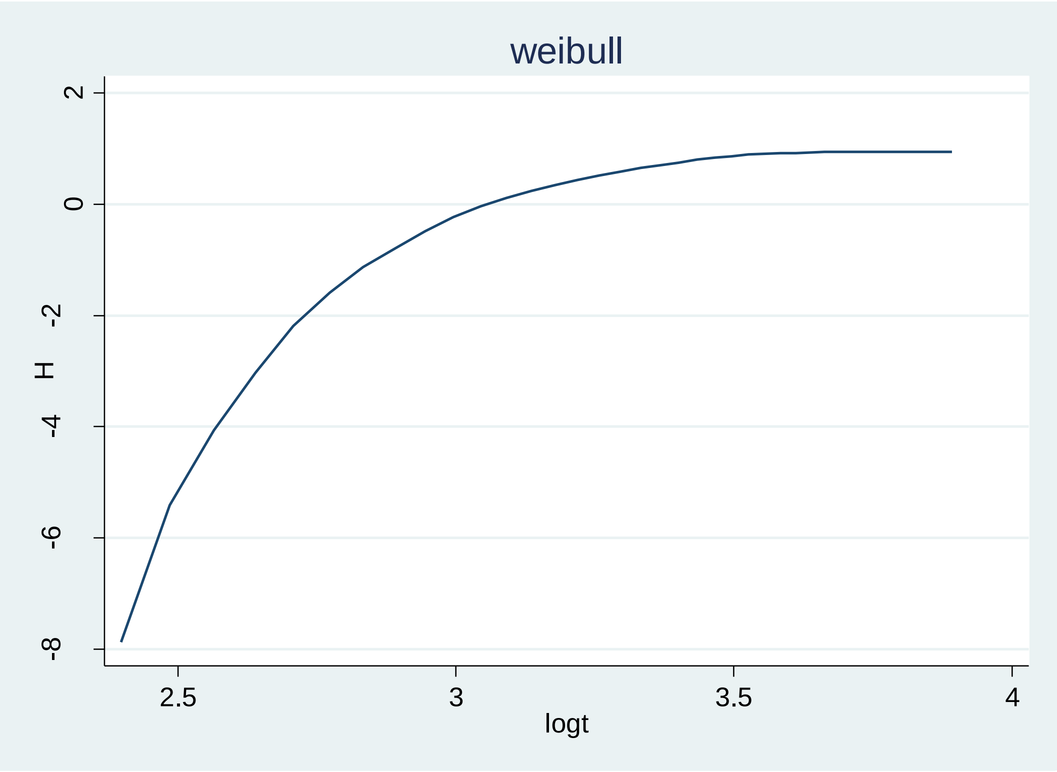
The acceleration factor for Muslim women was estimated to be 0.984 with 95% confidence interval (0.975, 0.993). The 95% confidence interval does not included one. This shows that women who followed Muslim religion shortened age at first birth by 0.984 at 5% level of significance.

The estimated coefficient of contraceptive user women was 0.036. The sign of the coefficient is positive which implies extended age at first birth. Hence, the age at first birth for contraceptive user women extended by a factor of 1.037 than the reference category (nonuser women) at 5 % level of significance.

The acceleration factor of employed women was 0.990. The 95% CI of acceleration factor (0.982, 0.997) does not include one. This means that employed women had shorter age at firs birth than unemployed women.

The confidence interval of the acceleration factor of media exposed women was (1.001, 1.017), does not include 1, indicating that media exposure is also significant prognostic factor for age at first birth. It extends age at first birth by a factor of 1.009 at 5% level of significance.

In the covariate husband/partners educational level, the estimated coefficient for secondary and higher was 0.014 and 0.030 respectively. The sign of the coefficients were positive indicates that women who had secondary and higher educated husband/partners had extended age at first birth by 1.014 and 1.030 respectively than women who had uneducated husband/partners.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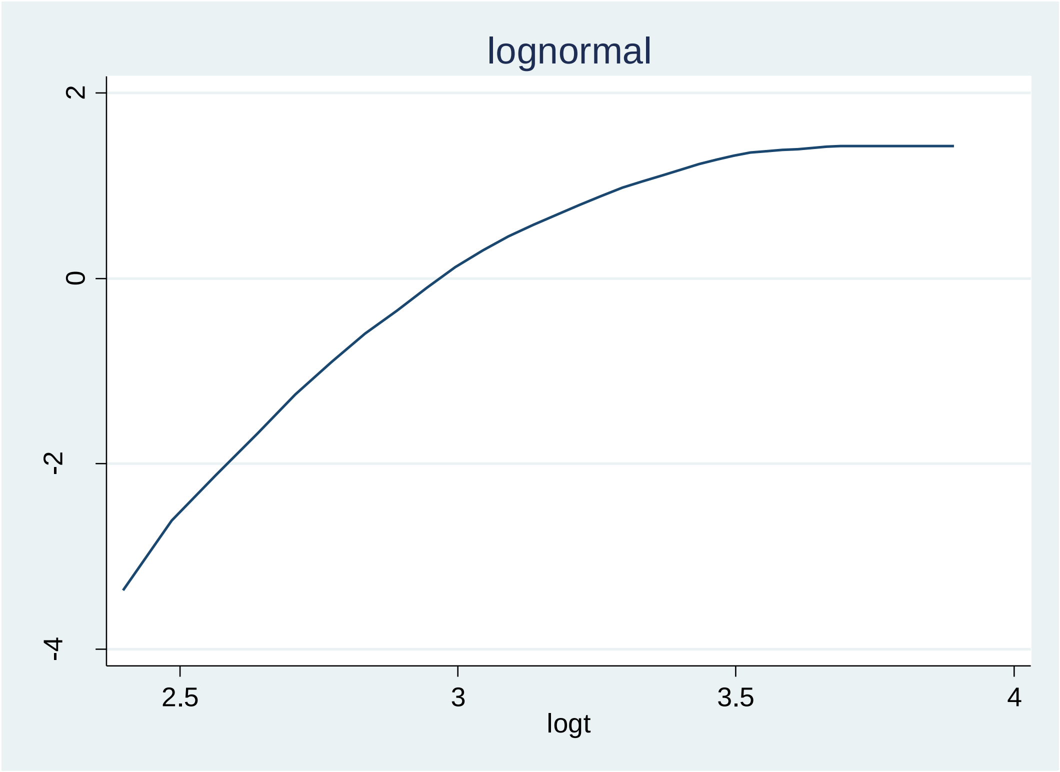
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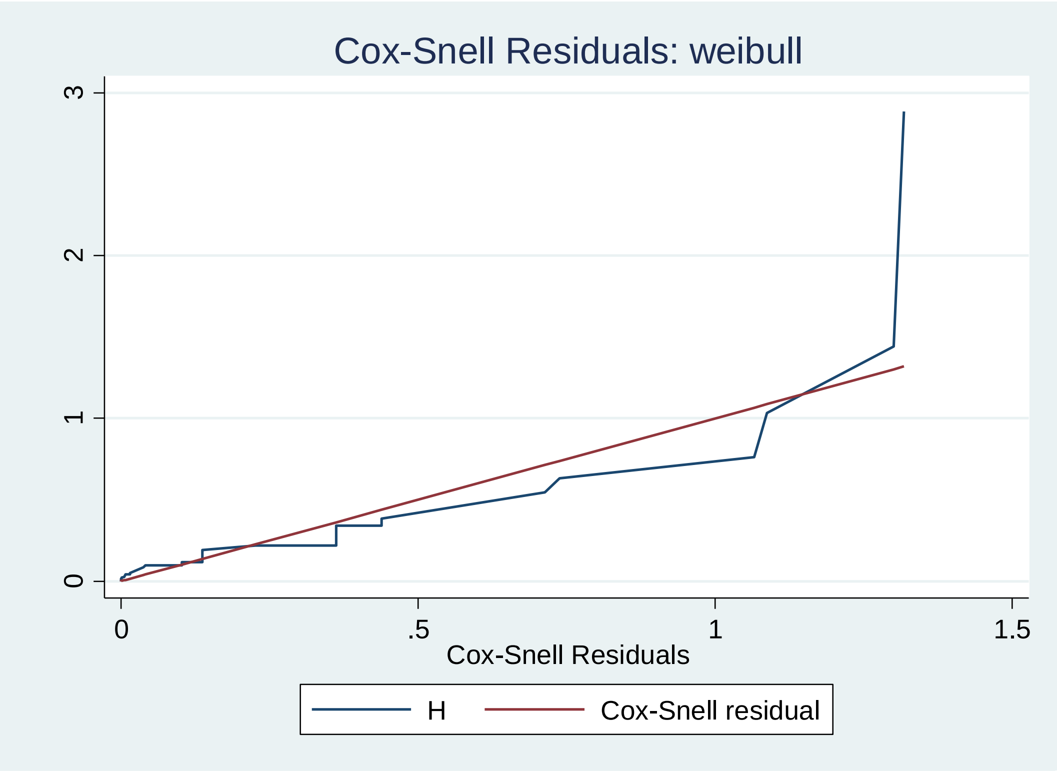
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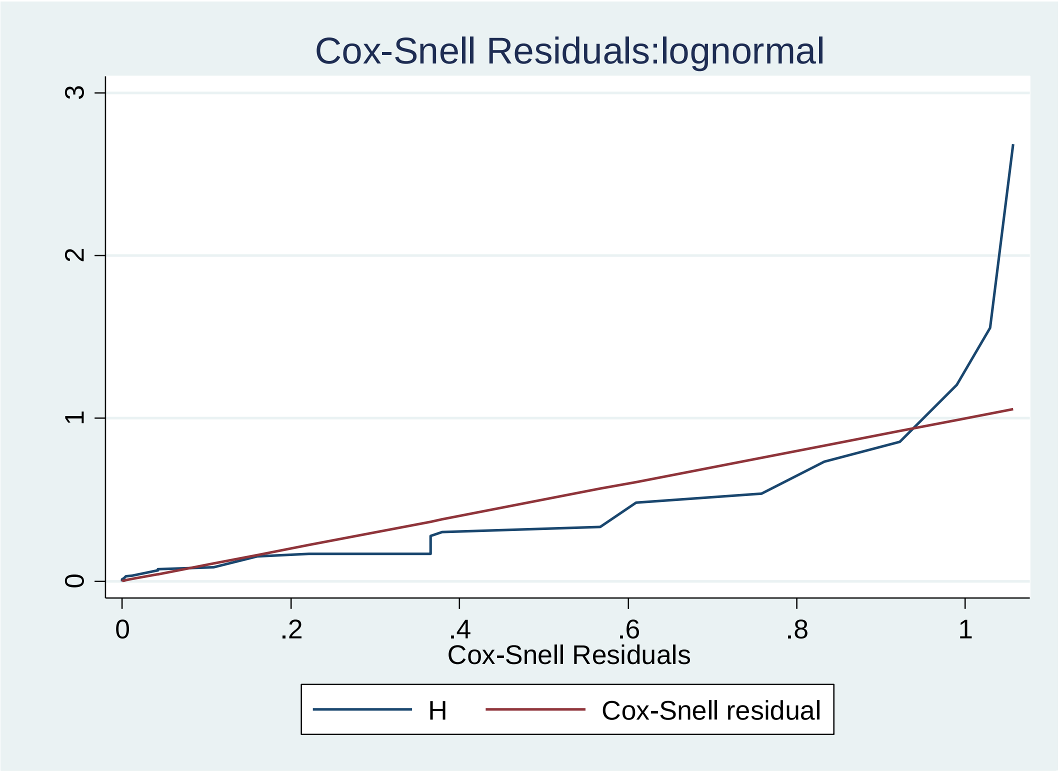
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Figure 4.10: Cox±Snell residuals to evaluate model fits of Weibull, lognormal and log-logistic models

4.8 Discussion

The main aim of the study was to identify determinant factors of age at first birth by applying parametric survival models. We considered two parametric models (AFT and shared gamma frailty) with three parametric baseline distributions (Weibull, lognormal and log-logistic).

Univariate and multivariable survival models were employed to examine the factors that determine age at first birth. Factors/variables considered in the study were region, place of residence, religion, women educational level, women working status, husband/partners educational level, contraceptive use, media exposure, husband/partners occupation, age at first sex, age at first cohabitation, wealth index and sex of household head. In the univariable results given in Appendix1 all variables except husband/partners occupation were significantly associated with age at first birth in all models at 25% level of significance. The significant variables in the univariate analysis were included in multivariable analysis.

This research also shows that there was a clustering (frailty) effect on age at first birth which might be due to the heterogeneity in region from which the women came from, assuming women coming from the same region share similar risk factors related to age at first birth, indicating that it was important to consider the cluster effect.

The comparison of the two parametric models was done by using AIC criterion. Where a model with smallest AIC was taken to be the most appropriate. Accordingly, log-logistic gamma shared frailty model which had AIC value of 2125.545 was the most appropriate model to describe the age at first birth data.

Multivariable analysis using log-logistic model shows that women educational level, religion,contraceptive use, age at first cohabitation, age at first sex, women working status,