DEBRE BERHAN UNIVERSITY

# MULTILEVEL COUNT REGRESSION MODELING ON DETERMINANTS OF FERTILITY AMONG REPRODUCTIVE AGED WOMEN IN ETHIOPIAN


BY :

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# DECLARATION

The undersigned hereby certifies that the thesis is entirely original with no submission for credit toward a degree from any other university, and that all references to materials utilized in the thesis have been properly cited.

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This paper have been submitted for examination with approval university advisors

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# APPROVAL SHEET

This is certifies that The thesis prepared by Birhan Mulugeta, " Multilevel Count Regression Modeling On Determinants Of Fertility Among Reproductive Aged Women In Ethiopian" which was turned in as part of the requirements for a master's degree in Biostatistics partially fulfills all university rules and accepted standards for originality and quality.

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## Table of Contents

# List of tables

## LIST OF ABBREVIATIONS

| | |
|---|---|
| AIC | Akaike information criteria |
| BIC | Bayesian information criteria |
| CSA | Central statistical Agency |
| DIC | Deviance Information Criteria |
| DF | Degree of Freedom |
| EDHS | Ethiopia Demographic and Health Survey |
| EMDHS | Ethiopia Mini Demographic and Health Survey |
| LL | log likelihood |
| LRT | Likelihood ratio test |
| MLM | Multilevel Model |
| MLNB | Multilevel Negative Binomial |
| MoH | Ministry of Health |
| NB | negative binomial |
| NBRM | Negative Binomial Regression model |
| PRM | Poisson Regression model |
| SNNP | South Nation,Nationality and people |
| WHO | world health organization |

## ABSTRACT

***Background****: Fertility is one of the elements in population dynamics that has a significant contribution towards changing population size and structure over time. Following Nigeria, Ethiopia is the second most populous country in Africa. Determining the factors that influence fertility is essential to developing new policies to improve maternal and child health, minimize high rates of population increase fertility in Ethiopia. The main aim of this study was to explore socio economic and demographic factors of fertility in Ethiopia among married women in the Reproductive age group using a count model.*

***Methods****: The data was taken from the 2019 EMDHS data, which was gathered representatively across Ethiopia's two city administrations and all administrative areas. A multilevel count model was used to investigate the high risk variables associated with high fertility in Ethiopia with a response variable of the number of living children ever born.*

***Results****: According to the findings of the respondents' descriptive study, women have an average of 4.36 living children per mother. The dispersion parameter is examined using the negative binomial regression count model, and the results indicate that it is not significant at the 5% level of significance. The predictor variables, mother' place of residence, region ,religion, wealth index, age at first birth, ,current age, contraceptive use, marital status, sex of household head, age of household head and age at first birth were found significant determinants at 5% significance level. The initial plot of the expected number of live births versus the different predictors showed regional variations in fertility in Ethiopia. Furthermore, the multilevel analysis demonstrated that, at the 5% level of significance, the variance in the number of living children per mother to be 0.220 with a standard error of 0.1003.*

***Conclusion****: In comparison to the Negative Binomial model, it was discovered that the Poisson Regression Model is more appropriate to the data. The single level Poisson regression model's results indicated that Somali regions had the greatest rate of fertility. To minimize Ethiopia's high fertility rate, it is critical to encourage women to use contraceptives and to wait until marriage in order to raise the age at first birth. Regions with high reproductive capacity should receive extra consideration.*


***Key words****: Count models, Multilevel Analysis Fertility, living children*

# 1. INTRODUCTION

## 1.1. Background of the Study

Fertility is one of the elements in population dynamics that has a 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, and the decline in birth rates, which was already modest, has slowed even further over the past decade (Bongaarts, 2008; Casterline, 2001). About 8% of the world's population lives in "high-fertility" countries that have experienced only limited fertility decline to date. Most of these countries are in sub-Saharan Africa (UN, 2015).It describes a population's real capacity for childbirth, which serves as both a primary explanatory factor in population dynamics and a primary mitigating factor against population attrition due to death (CSA, 2021). In the same way, it is a count of the number of living births among fertile women who are of childbearing age. Up until the point of data collection, all live births from married women are included. Changes in fertility lead to fluctuations in the rate of natural increase and have a significant impact on the age structure of a nation's population when there is no significant migration, regardless of mortality (*An Overview of the Determinants of High Fertility in Ethiopia | Ethiopian Journal of Development Research*, n.d.).

The world's population is expanding quickly as a result of the increased birth rate; in the next 40 years, the population of Sub-Saharan Africa (SSA) is expected to more than double from its current level (Lam & Elsayed, n.d.). In many communities around the world, having children is an essential element of the family formation process and an important cause of population change (CIA (2011), Feyisetan and Casterline (2000), and DeRose and Ezeh (2005)). For instance, a national policy was adopted in 1993 as part of Ethiopia's efforts to promote economic development. Its goal was to reduce the number of children per woman in both urban and rural areas from six and eight in 1993 to four in 2015The macro impact of population size is dependent on the socioeconomic behavior of individual households, according to other empirical studies like Bongaarts (2008) and Muhoza, Broekhuis, and Hooimijer (2014). For this reason, any national policy aimed at changing the population will need to identify the factors that influence the desired number of children in the household (Tadesse and Asefa (2001)).

In the sub-Saharan African countries, Population experts have raised concern about the demographic developments, especially the context  of the millennium period when many countries of the worldwide saw a stall in the decline in fertility (Bongaarts (2006), Bongaarts (2008), Westoff and Cross (2006), and Shapiro and Gebreselassie (2008). The total fertility of the population in sub- sahaRA Africa (SSA) is now 4.7 children per women, Africa continues to have a higher number of living children(H. Kiser & Hossain, 2019a). Additionally, African women still give birth to five children on average, around two third of these countries are at or below the replacement threshold (Garenne (2008) and Harper (2015)). Garenne (2008) and Bernstein et al. (2004) have compared the unrealized family planning target and the modernization process to Africa's current fertility rate. Urbanization, industrialization, and income levels all contribute to the modernization process. For example, women are more likely to have more children in locations where contraception was not previously commonly utilized (Dyson and Murphy, 1986).

Among African countries, Ethiopia is one of the developing countries with high fertility and rapid population growth rate. The country’s population in 2016 was estimated around 100 million (CSA,2016), placing it the second-most populous country in sub-saharan Africa. The fertility rate in Ethiopia is a rapidly growing population, and the high fertility rate among women is a significant contributor to this growth. The average number of children per woman in Ethiopia is much higher than the global average, and this has significant implications for the country's economic development, social welfare, and environmental sustainability. Global fertility, as reported in the 2015 assessment of world population projections, has reached 2.5 children per woman.

Ethiopia, being one of the developing countries where subsistence agriculture is the major economic activity, families often prefers a large number of children since they are considered as an economic asset rather than liabilities. In rural areas, parents want to have a large number of children to get assistance in farming activities (Bairagi, 2001) and emotional as well as economic support during old ages (Fapohunda and Todaro, 2000).

In traditional societies, children are also expected to strengthen the extent of kin relations, which implies not only economic benefits but also physical protection. Like many countries in sub-Saharan Africa, traditional norms and values in Ethiopia are in favor of high fertility. Having many children is considered as a virtue and respect of God in a number of Ethiopian rural communities (Desta and Seyoum, 1998).

The Ethiopian government has been making several efforts to reduce fertility levels since 1993, the first time an explicit national population policy aimed at reducing the total fertility rate from 7.7 children per woman to 4.0 by 2015 was launched (NPO, 1993). Increasing age at first marriage to at least 18 years, enhancing women‟s status through providing them with better employment and educational opportunities, expanding family planning services and information, communication and education on ways and means of limiting family size are some of the strategies designed to implement the population program (Assefa, 2001).

Determining the variables impacting the number of children among Ethiopian women is crucial for policymakers and researchers to develop effective policies and programs aimed at addressing issues related to population growth, family planning, and maternal and child health. Several demographic and economic factors influence the number of children. These various factors that influence the number of children a woman has in Ethiopia. These can be broadly categorized into cultural, economic, social, and individual factors. One of these factors was discovered to be women’s educational status. Because having more children reduces the opportunity cost of obtaining higher education, women who have greater educational standing desire fewer children overall. Furthermore, the number of children among young couples is comparatively higher when labor demand is strong and supply is low, suggesting a close relationship between the timing of childbearing and economic conditions (C. V. Kiser et al., 1968).The average number of children is negatively impacted by the mother's level of education; married women have the most children overall (Rahman et al., 2022).

The Ugandan study indicates that when respondents' and their husbands' educational attainment increases, the number of children declines. The study found that women's delaying marriage and raising their levels of education also considerably reduced the number of children born between 2006 and 2011. There have been fewer children in recent decades. Because initial marriages will occur at an older age if secondary school completion rates continue to improve. Education, employment, and food security were found to be significant causal variables for childbearing among women in another study (Haque et al., 2015). In a similar vein, reproductive women in Semnan, Iran found that the birth level had a highly substantial impact on the number of children they eventually produced (Saadati, 2015).

The place of residence is another independent predictor; a research conducted in Botswana found that women who lived in cities/ towns and urban villages had, respectively, 11.2% and 6.8% fewer children than women who lived in rural regions(Rahman et al., 2022). The number of children born is also influenced by age. Younger women have lower purposes for having children, although this is stronger among those who reside in rural regions and have larger families, according to studies done in Korea and Japan (Matsumoto & Yamabe, 2013). As the number of age groups decreased, the percentage of children also decreased steadily. Compared to other age groups, women in the 45–49 age range have more children[(H. Kiser & Hossain, 2019a) (Rahman et al., 2022)].

Women who watch television at least once a week have 9.9% fewer children than women who do not watch any television at all, while non-working mothers have more children than working mothers. Married women have the highest fertility rate; they have 21.7% more children than single women (Rahman et al., 2022). There was a substantial correlation between the wealth index and the number of children. The global fertility rate has dropped dramatically due to social development, and now stands at under 2.5 children per woman (Gauthier et al., 2004). Ethiopia and other developing nations find this velocity of transition to be startling, in addition to industrialized nations.

Ethiopia has seen an increase in fertility, according to several studies carried out there. Research carried out in southern Ethiopia found that 69.1% of people had high fertility 15. In a related study conducted in Addis Ababa, central Ethiopia, 72.4% of participants reported having a high fertility rate [16].Education status, mothers employment, age, place of residence, marriage, contraceptive use, were the major factors associated with fertility rate.

## 1.2. Statement of the Problem

The mechanism of factors affecting fertility is intermediate variables influence fertility directly, while socio-economic and demographics variables affect fertility indirectly through intermediate variables (Bongaa rts 1978). Some of these factors could be literacy status, occupation, religion, wealth status, place of residence, household headship, contraceptive use, region, reproductive life span and desired number of children (Behrman, J. R. and Wolfe, B. L.(1984,), (Angeles, 2008).

Most studies have concentrated on family planning as a general measure for fertility preference as much as it has its flaws. Collecting information on family planning as a measure of fertility preference can be relatively complex. Often it is difficult to get objective responses as questions on family planning are hypothetical in nature. Respondents, especially those illiterate or with little education may find it difficult to understand these questions (Zhang, 2007). In consideration of the above mentioned circumstances this study uses the preferred number of living children among fertile women in Ethiopia as the response variable.

Several studies investigated determinants of fertility in Ethiopia using some set of variables and statistical methods such as logistic regression (ordinary logistics regression), linear mixed model (LMM) (Ayele, 2015), Spatial (Yitayal Melese & Bewuket Zeleke, 2020) survival analysis, and linear regression models (Mekonnen & Worku, 2011a).Since, Poisson Regression Models (PRM) and Negative Binomial Regression Models (NBRM) have been demonstrated to be statistically more appropriate as the number of live children (NLC) data is a count data (Poston, 2002).

On the other hand, the data exhibits a hierarchical nature in the distant parts where women are nested below the enumeration area and each enumeration area is layered below the region. The multilevel data structure presents challenges for all of the previous basic statistical models and techniques, such as regression models that break the independence and normality assumptions of errors with constant variance(Harttgen & Misselhorn, 2006),((Saporta, 2006). If the underlying dependency resulting from the multilevel nature of the data is not corrected inside the simple regression models, when heteroscedasticity increases. In these situations, multilevel models as opposed to standard models have to be introduced in order to take into account the direct influence of both individual and group level variables. Numerous research have limited multilevel models for hierarchical data analysis [(Jula, 2014), (Hasinur Rahaman Khan & Shaw, 2021)]. In light of above literary works, this study focused on variables influencing married women's fertility in Ethiopia using a multilevel analysis framework and data from the Ethiopian Mini Demographic and Health Survey (EMDHS 2019).

Moreover, the previous studies have investigated the determinant factors associated with maternal health, infant health and other socioeconomic status of mothers using the 2016 EDHS data set. However, thus studies were not considering the factors like distance from health facility, type of birth and vaccination. Due to inaccessibility of health facilities and contraception use, the number of children was high. Therefore, this study tries to investigate the major socio-economic, demographic, health and environmental proximate factors including distance from health facility, influence number of children in Ethiopia. Generally this study will fill the gap and present new and available knowledge for different stakeholders.

This study to answer the following research questions:

- ✔ What are the determinant factors associated with the number of living children among Ethiopian married women?
- ✔ Which regression model is an appropriate fit to analyze the number of children from EMDHS 2019 data?
- ✔ What is the average number of children among Ethiopian women of reproductive age?

## 1.3. Objectives of the study

### 1.3.1. General objective

The objective of this study was to identify the determinant factors that influence fertility among Reproductive aged Women in Ethiopian.

### 1.3.2. Specific Objectives

The specific objectives of this study are:

- To explain Ethiopian Reproductive aged women's fertility status
- to determine how Reproductive aged women's fertility varies across Ethiopian region
- To identify appropriate count regression models in order to analyze the number of living children among Ethiopian Reproductive aged women

## 1.4. Significance of the study

The findings from this study are useful in many ways. The findings are believed to be useful for policy making, monitoring and evaluation activities of the government and different concerned agencies. This study is significant for several reasons.

Firstly, the study would contribute to the existing literature on fertility rates in Ethiopia by providing a comprehensive analysis of the various factors that influence fertility rates. While previous studies have examined some of these factors, such as education and access to healthcare, this study will provide a more nuanced understanding of the complex interplay between individual, socio-cultural, and economic factors that affect fertility rates. Secondly, the study will provide insights into the role of gender roles and expectations in shaping reproductive behavior among Ethiopian women. This is particularly important given the patriarchal nature of Ethiopian society and the traditional gender roles that women are expected to fulfill.

Finally, the study will provide practical recommendations for policymakers and stakeholders to address the factors that influence fertility rates among Ethiopian women. These recommendations will be based on empirical evidence and will be tailored to the specific context of Ethiopia, taking into account the country's unique socio-cultural and economic factors. By implementing these recommendations, policymakers and stakeholders can work towards reducing Ethiopia's high fertility rate and improving reproductive health among

Ethiopian women and their families. These recommendations can inform the development of effective interventions that address the root causes of high fertility rates in Ethiopia. Furthermore, it can serve as a baseline study for future researchers in the field.

### 1.5.Limitation of the Study

Numerous research on the factors that influence fertility in various nations have been carried out. Only a few of the factors that influence fertility in Ethiopia are included in this study because data gathering methods missed certain important variables, such as age at first marriage. Furthermore, the study is restricted to those who were married at the time the data was collected.

# 2. LITERATURE REVIEW

## 2.1. Concepts of Child fertility

High fertility experience in sub-Saharan Africa is as a result of a large desired number of children. According to (Hoffman et al., 2020) the value of children is considered as a major driver facilitating the study of fertility change. One of the three main factors in population dynamics that affects the country's population size and composition is fertility. Differential fertility behavior and fertility levels in different areas and among population strata or characteristics have been among the most pervasive findings in demography (Ramesh 2010).

The biological replacement and preservation of the human species is based on human fertility. A father and a mother come together to produce children, and in order to maintain a stable population, they plan to have at least two children, which will replace them. In fact, fertility has a considerable expansionary force in population dynamics since it is a major counteracting force to population attrition from mortality. In a case where the two children turn out to be girls, most couples in Africa try to give childbirth more chances until they have mixed sexes since male child determines continuation of family line (Hoffman et al., 2020)

Westoff (2010) found that among women under 25 who had not married at the time of the survey, DHSs conducted across several sub-Saharan African countries between 1998 and 2008 showed that the mean desired number of children stated by women of reproductive age in West and Central Africa ranges from 4.8 in Ghana to 9.2 in Chad and 9.1 in Niger. Compared to Western and Central Africa, the countries of Eastern and Southern Africa have lower birth rates.

## 2.2. Theoretical Reviews of Literature

The biological continuation and repair of the human species on Earth are attributed to fertility in the human population. The reproductive span, or the time a woman can have children, is often measured in demographic studies between the ages of 15 and 49. A woman in the reproductive age group may therefore be fertile or not. The age at menarche and the age at menopause are the primary happenings or events linked to fertility.

Numerous scholars have proposed several ideas regarding the reduction in fertility. The quality-quantity trade-off is the main focus of the first strategy, which was put forward by (G. Becker et al., 1973). The claim made here is that having more money could result in having fewer children. However, it also hinted at a low degree of economic progress brought on by high rates of birth and child mortality.

considered sub-Saharan Africa The difference in the rate of childbearing between married women living in rural and urban areas was found to have decreased by almost 19%, according to DHS data (Bove & Valeggia, n.d.). A review of the literature reveals that several studies have been conducted on fertility and reproductive health in Ethiopia highlights several factors that influence the number of children among Ethiopian women. Policymakers and development practitioners need to take a holistic approach that addresses these multiple factors in order to reduce fertility rates and promote reproductive health among Ethiopian women.

The menarche and menopause are the two extremes of this phase of life, which is known as the fecund period. In demographic research, the childbearing years for women are typically considered to be between the ages of 15 and 49. In this way, a woman who is fecund may or may not also be fertile, while the opposite is true for the other. Age at menarche and age at menopause are the primary occurrences or phenomena linked to fertility. It has been discovered that getting married later affects fertility.

(Bongaarts, 1978)the main categories of factors that affect fertility are proximate (direct) and distal (indirect) factors. The distal determinants are socio-cultural factors, which affect fertility indirectly by affecting bio-behavioral factors. The proximal determinants are biological factors, such as sexual activity, use of contraceptives, length of postpartum infecundability, abortion, and sterilization, which affect fertility directly. In addition to contraception control behavior and attitudes , other factors which determine the number of children among Ethiopian women include socio-economic, demographic, cultural, and economic factors in shaping reproductive behavior among Ethiopian women.

### 2.2.1. Socio-economic implication

Socioeconomic factors are the independent variables that act through proximate determinants to influence the level of morbidity and mortality. They can be grouped in to individual level, household level and community variable, socio-economic factors may affect, directly and indirectly, environmental, behavioral, nutritional and demographic risk factors with the exception of age and sex (Mondal and Mani, 2012).the study can shed light on the socioeconomic factors that impact family size, such as educational attainment, financial stability, religious beliefs, women's employment engagement, access to healthcare etc. (Samson and Mulugeta 2009). Women's age (Bongaarts 1978), education (Sharma, 1998), employment status (Mason and Palan 1981), place of residence (Abdul Hakim 1994), use of contraception (Haile and Enqueslassie 2006), religion (Caldwell and Caldwell 1987:409), and economic status (Hakim and Miller, 1996) are among the factors that affect fertility.

According to a study by Mekonnen and Worku (2011), socio-demographic factors such as age, education, religion, and marital status have been found to be significant predictors of fertility rates among Ethiopian women. A study by Tilahun et al. (2018) identified several factors that influenced fertility among Ethiopian women, including age at first marriage, age at first birth, contraceptive use, and religion. Martin (1995) examined the association between women's education and fertility in 26 countries using the DHS data from African and other developed countries. Mother‟s education has frequently been used as a proxy indicator of socio-economic status in international surveys and studies. The studies have shown that women who are younger, have a lower level of education, and live in rural areas tend to have higher fertility rates compared to older and more educated women. The researcher found that higher education level was reliably related to low fertility of women in those countries. The study revealed that women who had no formal education had a higher fertility rate compared to those who had at least primary education.However, mother‟s education is also thought to be associated with hygiene, care seeking, and treatment of illness behaviors pertaining to early childhood morbidities (Stalling, 2004). Kravdal (2002) well-thought-out the case of 22 countries in the sub-Saharan African region and stated that the average fertility for these countries would be one child less if women's education were encouraged beyond the current level in the region to the current high level. Additionally, married women are more likely to have more children than unmarried women.

Cultural factors such as religion, ethnicity, and traditional gender roles also play a role in shaping reproductive behavior among Ethiopian women. According to Caldwell and Caldwell (1987), when African women express their desired number of children, they often invoke the will of God. This means that they believe God can allow them to have as many children as they are biologically capable of carrying the load. For example, studies have found that Muslim women tend to have higher fertility rates compared to Christian women. Similarly, women from certain ethnic groups, such as the Oromo and Amhara, tend to have higher fertility rates compared to other ethnic groups.

Traditional gender roles that expect women to bear children and prioritize motherhood over other pursuits also contribute to high fertility rates in Ethiopia.

Economic factors such as income, employment, and access to healthcare also influence fertility rates among Ethiopian women. Studies have shown that women with higher incomes and those who are employed tend to have lower fertility rates compared to those with lower incomes and who are unemployed. Access to healthcare services such as family planning and maternal health services also plays a critical role in reducing fertility rates among Ethiopian women. The Chicago-Columbia model of economic fertility was developed from studies (G. S. (Gary S. Becker, 1976) and (G. S. Becker & Lewis, 1973) Children's "quantity-quality trade-off" is a concept introduced by Becker in 1976. In order to analyze the desire for children in the household, he makes the assumption that children are similar to consumer durable goods. Additionally, he believed that the preference for children was exogenous, meaning that it was unrelated to economics. The demand for children is influenced by women's salaries and household income. When the substitution impact outweighs the income effect, Becker (1976) claims that increased family income leads to fewer offspring of higher quality.

The "Chicago Columbia" model's fundamental premise is that households are capable of making decisions that take into account both the quality and number of their children. Additionally, Becker (1960) makes the assumption that the income elasticity of the number of children in industrialized nations is small but positive. Due to social pressure, however, when wealthy (or poor) families are required to maintain the quality of their children in accordance with their status, the income elasticity of the children's quality is rather high.

According to (Easterlin & Crimmins, 1985)a household's actual number of children will be fewer than its projected number of children if expected income is higher than real income. According to him, a couple's decision on the anticipated number of kids "depends on the parents' childhood experiences. For instance, spouses and husbands with large families tend to have more children.

### 2.2.2. Demographic factors

Understanding the factors that influence the number of children can help policymakers and researchers predict and plan for changes in population demographics. The effect of these factors on health is complex and is conditional by a wide range of characteristics and behaviors. For example, maternal age, marital status, type of birth, birth interval. These factors have an effect on child fertility. This can be especially important in countries with rapidly growing populations or aging population.The study conducted on determinants of number of children by using Univariable and multivariable multilevel logistic regression models.

In the Matlab region of Bangladesh, Pritchett (1994) discovered that the average fertility planning efforts were only slightly affected by the use of contraceptives and family planning, as seen by the 0.22 to 0.37 births per woman reduction in the number of children born. Then, (Bongaarts, 1994) contended that Pritchett did not find a significant independent effect of family planning programs on fertility outcomes because family planning initiatives influence fertility desires by disseminating knowledge in addition to facilitating access to contraceptives. Pritchett's findings regarding the impacts of family planning on fertility have been validated by numerous recent micro-level studies ((Bongaarts, 2011), (Joshi & Schultz, 2013)& , and Molyneaux & Gertler (2000)). Among others, Bongaarts (2011) confirmed that complete family planning programme execution, including the distribution of contraceptives and essential information, could solve high fertility. Two arguments have resulted from the use of family planning in fertility control: first, opponents of the method contend that family planning programs can close the significant gap between intended and actual fertility in African nations by preventing unplanned pregnancies.

## 2.3. Empirical Studies on the determinants of the number of children

Several studies have been conducted to determine the factors that influence the fertility rate among Ethiopian women. A study by Alemayehu et al. (2015) found that maternal age, education level, and contraceptive use were significant predictors of fertility rate.

A linear model (OLS) was used in the studies by (Behrman & Wolfe, 1984), (Ainsworth et al., 1996), (Osili & Long, 2008), (Kabeer, 2001), Kabir et al. (2001) to determine the factors that affect women's fertility. Behrman and Wolfe (1984) attempted to relate both “Chicago-Columbia‟ and “Pennsylvania‟ models using data on women who completed their fertility. Using data on women who finished their fertility, Behrman and Wolfe (1984) attempted to reconcile the "Chicago-Columbia" and "Pennsylvania" models.

In Nicaragua, data on women were gathered between 1977 and 1978, and they used the number of a woman's number of live children as the dependent variable. Education for women and The variables in the "Chicago-Columbia model" were household income. As biological supply factors of the "Pennsylvania model," they included women's health condition, age, age at first marriage, age at first cohabitation, average length of breastfeeding, and average calorie intake. As expectation-building variables for the "Pennsylvania model," they also included the type of marriage, the number of siblings, the birth rate, and the place of upbringing. Both the "Chicago-Columbia" and the "Pennsylvania" variables contain significant determinants, according to the researchers. They point out that models built solely on the "Chicago-Columbia" model may overestimate the impact of women's education and household income, sometimes producing misleading results, because the "Chicago-Columbia" model doesn't emphasize supply-side variables, taste, and other factors for estimating fertility.

Ainsworth et al. (1996), Osili,and Long (2008) conducted studies to determine whether women's education had a detrimental impact on fertility in African nations. In contrast to the preceding study, the dependent variable in these studies' models uses the number of children ever born to each mother. In fourteen sub-Saharan nations, the fertility of women was calculated by Ainsworth et al. in 1996.

In thirteen sub-Saharan nations, they discover that women's education has a negative correlation with fertility; Senegal is the only exception. Osili and Long (2008) looked at whether the introduction of universal primary education was the root of the negative association between fertility and education, using the 1999 Demographic and Health Survey from Nigeria. They reasoned that since fertility choice interferes with education, education is endogenous to fertility determination. For the years that women were in school, they used exposure to the universal curriculum as an instrumental variable (IV).

They evaluated the model in both the OLS (without instrument) and IV variable approaches using the difference in difference method. They did discover that the coefficient estimates are negative for women's educational attainment in both instances, although the IV estimates are larger than the OLS estimates.

Children born were also employed by Kabeer (2001) and Kabir et al. (2001) as an indicator of women's fertility. Using the 1989 Bangladesh Fertility Survey, Kabeer (2001) developed a distinct model for each age group (i.e., 12 to 19, 20 to 40, and 40 and more). She came to the conclusion that reproduction is adversely correlated with men’s and women's education, wealth, and employment status across all age groups and that Muslim women had higher fertility than women who adhered to other religions. She also discovered a difference between rural and urban areas for people aged 20 to 40 and older, but not for those aged 12 to 19. Data sets from the Bangladesh Demographic and Health Survey from 1993–1994 and 1996–1997 were used by Kabir et al. (2001). For each data set, they evaluated fertility determinants independently. They discovered that women's access to the media, education, work, and place of residence all have a detrimental impact on their fertility.

According to a study conducted in China, having a small family is preferred by those who are younger, live in cities, and have higher levels of education (Ding & Hesketh, 2006)A comparable study found that having a high mean number of children was likely for both men and women with low levels of education (NSF 2006).According to (Dommaraju & Agadjanian, 2009), changes in Bangladesh's fertility regime are typically brought about by changes in illiterate women's reproductive habits rather than changes in women's status.

In his research on the causes of educational differences in fertility among 30 sub-Saharan countries, (Bongaarts, 2010) discovered that women with secondary or higher education have on average lower fertility than women with no education (3.4 vs. 6.3 births per woman), which is also the case in desired family size (3.7 vs. 5.6 births per woman). Furthermore, there are variations according to education level in the connections between reproductive indicators. Increasing levels of education lead to lower fertility at a given level of contraceptive usage, higher contraceptive use at a given level of demand, and higher demand at a given level of desired family size. As a result, education has a negative impact on a woman's preference for having children.

Another study by (Gebremedhin et al., 2015) investigated the impact of income on fertility rate among Ethiopian women. The study found that women with higher income levels had a lower fertility rate compared to those with lower income levels. The authors suggested that increasing women's economic empowerment could be an effective strategy to reduce fertility rates.

The "Chicago-Columbia" model formed the foundation for (Wang & Famoye, 1997) investigation. For 1968 and 1989, they used US data from the Michigan Plan Study of Income Dynamics. They over-dispersion the dependent variable is the number of children in a family—in their analysis. As independent variables, they included women's work status, education, family income, ethnicity (white or non-white) dummy, and rural-urban dummy. Both the Poisson and the negative binomial models were estimated, and it was discovered that while both models provide similar estimates, the Poisson model has higher standard errors than the modified Poisson model. They discover that the level of education, occupation, and family income of the mother have a detrimental impact on fertility. Additionally, they discover that non-whites have higher fertility than whites.

(Atella et al., 2000) looked at the relationship between fertility and the likelihood that children will survive, as well as the ambiguity surrounding that probability. They examined data from the Human Development of India Survey conducted in 1994. Women's childbirth rates were employed as the dependent variable. They included the age, length of marriage, money, education, and religion of the wife and husband, as well as the frequency of deaths among children and the ambiguity around child survival rates. They used the village mean survival rate of children under the age of five as an expectation for child survival rate and the village variance of child survival rate under the age of five as a measure of uncertainty. Both the Poisson and Poisson hurdle models were applied.

(Miranda, 2010) argues that the double hurdle model is superior to the single hurdle model for fertility data from Mexico. He said that socioeconomic factors in Mexico have an impact on women's fertility decisions to switch from a low to a higher birth order. Employing information from the 1997 Mexican Survey of Demographic Dynamics as his data source, he applied the double hurdle Poisson model, utilizing the dependent as the total number of children ever born to a woman who reached full fertility. He used the age, place of birth, religion (Catholic), education, and ethnicity of the women as explanatory variables. He builds two hurdles for the model, the first at position zero and the second at position three. He discovered that Catholicism and education both lower women's chances of having more than three children. He discovered that Catholics have higher fertility than non-Catholics and indigenous language speakers have higher fertility than non-indigenous language speakers for women giving birth to more than three children in the south region.

(Kravdal, 2002) uses the Demographic and Health Surveys for 22 Sub-Saharan countries to build a discrete-time Hazard regression model. To investigate how the distribution of educational attainment impacts women's overall fertility, he ran a Monte Carlo simulation. For twenty-two countries, he makes estimates using two different models. The first is for women who give birth for the first time, and the second is for those who give birth more than once. In the first model, he tracks women over a two-year period who don't have children until their first birth, which occurs every three months. He also imitates the women who had higher-order births. As explanatory factors, he utilizes the average duration of education in each community, rural versus urban, the number of Muslims, the proportion of adherents of other religions, and the wealth indicator. He discovered that a woman's education has a significant impact on first-order births but a lesser impact on higher-order births. Additionally, he finds that the community's average duration of education has a detrimental impact on women's fertility.

(Sennott & Yeatman, 2012) found in their research in Malawi that events that affect one's financial situation can impact one's plans for having children in the future. For instance, losing a job might cause a woman to put off getting pregnant so that the family has time to get their finances back in order before welcoming a new member. On the other hand, a partner starting a new career can prompt a woman to start trying to get pregnant. Frequent shifts in reproduction preferences may also be a reflection of the economic ambiguity seen in developing nations like Malawi, where work opportunities may be intermittent or limited (Johnson-Hanks, 2005, 2007; Agadjanian, 2005). Numerous studies have shown a strong connection between work and intended fertility and behaviors associated with fertility. People in cities favor families with no children. The choice of family size varies locally, depending on where people live (Ali, 2000). Due to various societal patterns and behaviors, there are regional variations in fertility intentions. According to an examination of survey data from 17 Arab governments, urban and educated women are leading the fertility shift in the majority of these nations (Farid, 1996). Age at first marriage occurs early in Senegal, according to Size et al. (ND) in their research of women in both rural and urban Senegal. In metropolitan regions, 53 percent of women between the ages of 15 and 29 and over 49 percent of women between the ages of 40 and 49 were married before the age of 20. As opposed to this, 71 percent of rural women. An inverse relationship between the desire for more children and occupation was found by Ayehu (1998) in his study among the Meru of Kenya. He found that women married to husbands with higher occupation status were more likely to want to stop having children than women married to husbands with lower or middle-status occupations.

A study by (Yaya et al., 2018) examined the impact of access to healthcare on fertility rate among Ethiopian women. The study found that women who had access to healthcare services had a lower fertility rate compared to those who did not have access to healthcare. The authors suggested that improving access to healthcare services could be an effective strategy to reduce fertility rates and improve reproductive health outcomes in Ethiopia.

In addition, a study by (Mekonnen & Worku, 2011b) investigated the impact of marital status on fertility rate among Ethiopian women. The study found that married women had a higher fertility rate compared to unmarried women. The authors suggested that promoting delayed marriage and increasing access to family planning services could be effective strategies to reduce fertility rates among married women.

Overall, these studies suggest that several factors, including maternal age, education level, income, access to healthcare, and marital status, impact the fertility rate among Ethiopian women. Policymakers and healthcare providers can use this information to develop targeted interventions aimed at improving reproductive health outcomes and reducing maternal and infant mortality rates in Ethiopia.

# 3. DATA AND METHODOLOGY

## 3.1. Source of data

This research used the 2019 Ethiopia Mini Demographic and Health Survey (EMDHS) data to serve as the study's data source which is obtained from CSA Technical Working Group (TWG) serves as the umbrella advisor to the Federal Ministry of Health (FMoH). The main aim of the survey was to gather population-based data on important demographic variables in order to support programs for the advancement of maternal and newborn health in the health sector. It is the fifth significant survey with the aim of providing estimates for the relevant demographic and health variables. The survey was conducted from March 21, 2019, to June 28, 2019, based on a nationally representative sample that provided estimates at the national and regional levels and for urban and rural areas. The survey used a two-stage stratified sampling technique. Each region was stratified into urban and rural areas, yielding 21 sampling strata. In each stratum, samples from the enumeration areas (EA) were chosen separately in two stages. A total of 305 EAs (212 in rural areas and 93 in urban areas) were chosen in the first stage, with probability proportional to EA size and independent selection in each sampling stratum. A household listing operation was carried out for all selected EAs. The generated list of households was used as a sampling frame for the second stage's selection of households. In the second step of the selection process, a specific number of 30 households in each group were chosen with an equal likelihood of systematic selection. The survey interviewed 8,885 women of reproductive age (age 15-49). At the time of data collection were included in the study survey with the women having incomplete information.

## 3.2. Variables Included in the Study

In regression models there are two types of variables in the study, these are outcome (dependent) and explanatory (independent) variables.

### 3.2.1. Response Variable

The study's response variable is a count variable that represents the number of living children among the reproductive age of women (15-49), $Y_i$, as the dependent variable in the study.

### 3.2.2. Explanatory variables

A number of variables were chosen as predictors based on the literature. These factors were chosen for this study based on their possible significance.

**Table 3.1. : Descriptions of independent categorical variables are presented in tabular form as follows.**

| No | Description and Name | Categories |
|---|---|---|
| 1 | POR(Place of residence) | 0=Urban |
| | | 1=Rural |
| 2 | Region/Administrative city) include all nine regional states and two city administration in ethiopia. | 1=Tigray |
| | | 2=Afar |
| | | 3=Amehara |
| | | 4=Oromia |
| | | 5=Somali |
| | | 6=Benishangul |
| | | 7=SNNPE |
| | | 8=Gambela |
| | | 9=Harari |
| | | 10=Addis Ababa |
| | | 11=Dire Dawa |
| 3 | Current Age of mothers (Age)=Mother's age at the time of the survey conducted. | 1=15-19 |
| | | 2=20-24 |
| | | 3=25-29 |
| | | 4=30-34 |
| | | 5=35-39 |
| | | 6=40-44 |
| | | 7=45-49 |
| 4 | **Current Contraceptive**: in the form of "yes" if women are using contraceptives and "no if not at the time of the survey." | (0):User(yes) |
| | | (1):non user(No) |
| 5 | **Sex of household head(SHH) :** classified as Male and Female | 1=Male<br>2=Female |
| 6 | **Age of household head(AHH):** age group of household head | Continous |

| | | |
|---|---|---|
| 7 | **Economic status(Wealth index):** household economic status using CSA classification system | 0=Poor |
| | | 1=Middle |
| | | 2=Rich |
| 8 | **Religion**: the beliefs of the mothers | 1=Ortodox |
| | | 2=Catolic |
| | | 3= Protestant |
| | | 4= Muslim |
| | | 5=Traditional |
| | | 99=Others |
| 9 | **Marital status**: with category of | 1=Single |
| | | 2=Married |
| | | 3=Separated |
| 10 | **Age at first birth**: age of respondents | 0,<=15 |
| | | 1,=16-19 |
| | | 2,>=20 |
| 11 | **Education levels of mother(ELM):** with category of | 0=No education |
| | | 1=Primary |
| | | 2=Secondary |
| | | 3= Higher |

Source EMDHS 2019

## 3.3. Methods of Data Analysis

### 3.3.1. Count Data model

Counts are positive, unsigned integers. The only non-negative integer values that the observations can have are 0, 1, 2, 3, etc. These integers are produced through counting, not ranking. The Poisson distribution serves as the basis for the development of the count data model. Regression models for count data are frequently used in statistics to model response variables. The variable of interest in this study is a count variable. 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 when the response or dependent variable (number of children that women between the ages of 15 and 49 have) is a count (which can take on nonnegative integer values).

The appropriate models for count data can be divided into three categories: the count model for equal dispersion, the Poisson Regression model, and the count model common case of over dispersion includes; Negative Binomial Regression model (over-dispersion), Zero-Inflated Count Models (excess zeroes); Zero-inflated Poisson model, Zero-inflated Negative Binomial model, and hurdle model . Since the beginning of time, linear regression has been used to analyze count variables as continuous variables. The OLS linear regression model, however, might not fit count data with a positively skewed distribution well (Moghimbeigi et al., 2009).

There are four reasons to use the count model. First, the OLS linear regression model produces negative values, but count data are always larger than or equal to zero. In other words, OLS linear regression does not account for data being truncated at zero; thus, it could predict negative values which are meaningless (King, 1988 & Sturman, 1999). Second, one of the assumptions for validating statistical tests from OLS linear regression is the normality of residuals. Count data with a positively-skewed distribution are unlikely to satisfy this assumption. Third, the validity of hypothesis tests in the OLS linear regression model depends on assumptions about the homogeneity of variance of residuals that are unlikely to be met in count data (Gardner, & Shaw, 1995). Fourth, OLS linear regression is mainly for continuous dependent variables, not discrete variables, like count data. Due to the reasons mentioned above, using OLS regression to analyze count data may lead to conclusions that do not make sense for the data, such as impossible mean predicted values, and incorrect standard errors for significance tests and p-values. Using linear regression models for count data is very inefficient. It has inconsistent standard errors and may produce negative predictions for the number of events. The least square estimates with a logged dependent variable suffer from these problems and are biased and inconsistent as well.

Unlike in the case of a classical regression model, the response variable is a discrete with a distribution that places the probability mass at non-negative integer values only. Regression models for counts, like other limited or discrete variable models, are nonlinear with many properties and special features intimately connected to discrete-ness and non-linearity (Cameron and Trivedi, 2013). Despite the fact that count data regression modeling techniques have a rather recent origin, the statistical analysis of count data has a long history. Most of the early statistical count analyses concerned univariate independent and identically distributed random variables within the framework of discrete parametric distributions (Johnson et al., 2005). With these statistical models for handling count data, it is difficult to know which one to choose by just someone's intuitive feelings. proposed a comparative approach for handling count data by comparing different count regression models on how they fitted their count data using the Akaike Information Criterion (AIC) , and Bayesian information criterion (BIC) (Johansson, 2014) .

## 3.4. Statistical Models

In this study, the variable of interest is a count variable. When the dependent variable (number of children) 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. Unlike linear regression, count data regression models have counts as the response variable that can take only nonnegative integer values (Cameron and Trivedi, 2013). Numerous models have been developed specifically for count data (Long & Freese, 2006; Sano & Zvonkovic, 2005). These models can handle non-normality on the dependent variable and do not require the researcher to either dichotomize or transform the dependent variable. We shall focus on six of these models (Atkins & Gallop, 2007; Long & Freese, 2006; Sano et al., 2005): Poisson, Negative Binomial, Zero-inflated Poisson (ZIP), Zero-inflated Negative Binomial (ZINB). Hurdle Poisson regression model and Hurdle Negative Binomial regression Model (Harris et al., 2014).

### 3.4.1. Poisson regression model

In order to investigate the relationship between the count outcome variable and covariates can be modeled using a Poisson regression model. It is appropriate for representing the volume of events that take place over a certain amount of time or space. As the mean of the dependent variable declines, the Poisson distribution gets more and more positively skewed (Long et al., 2006) reflecting a characteristic of count data. However, because of its limiting presumptions, it frequently fails in practical applications.

According to (Sturman, 1999) The Poisson model must be tested under two significant presumptions: first, that events occur independently throughout time or exposure period; second, that the conditional mean and variance are identical. The relationship between a Poisson distributed response variable and one or more explanatory factors can be modeled using a Poisson regression model (Hinde, 1982). It is appropriate for representing the volume of events that take place over a certain amount of time or space. Over-dispersion occurs in practice when counts have more variance than the mean. This shows that Poisson regression is insufficient.

Other causes include counts with excess zeros or zero-inflated counts, since the excess zeros will give a smaller mean than the true value, and this can be modeled by using zero-inflated Poisson (ZIP) or zero-inflated negative binomial (ZINB). There are two common causes that can lead to over-dispersion: additional variation to the mean or heterogeneity. A negative binomial model is frequently used. An industry-standard framework for the analysis of count data is provided by the Poisson Regression Model. Let Yi represent counts of events occurring in a given time or exposure period or area with rate $\mu i$, Yi are poisson random variables with probability mass function (pmf) given below:

$$P(Y_i = y_i, \mu) = \frac{e^{-\mu i} \mu_i y_i}{y_i}$$ ------------------------------------------------------------------(3. 1)

Where $y_{i=}$ 0,1,2,3 and $\mu_i$ =1,2,3,…

where, Y denotes the ideal number of children for the i^th^ women in the given time or exposure period with mean parameter μi

$$\ln(\mu_i) = x_i^T \beta = \eta_i$$

Where, $X^T = (1, X_{1i}^T, X_{2i}^T ...)$ is the vector of explanatory variables and $\beta = (\beta_0, \beta_{1,} \beta_{2 - - -} \beta_p)^T$ is the vector of the unknown regression parameters.

Using maximum likelihood estimation, the regression parameters are computed. Based on a sample of n independent observations, the Poisson model's likelihood function is given by

$$l(\beta, Y_i) = \prod_{i=1}^{n} \frac{e^{-\mu_i} \mu_i^{y_i}}{y_i!}$$

The log-likelihood function is

$$l = \log(l(\beta)) = \sum_{i=1}^{n} [y_i \ln \mu_i - \ln y_i!$$

The partial derivations of the log-likelihood function are taken and set to zero to provide the likelihood equation for estimating the parameter. As a result, we arrive at the following first derivatives of l with regard to the underlying parameters:

$$\frac{\partial l(\beta)}{\partial(\beta_i)} = \sum_{i=1}^{n}(y_i - \mu_i)x_{ij}$$

When subsequent events happen independently and at the same rate, the Poisson regression model is suitable for modeling count data. But in reality, data features frequently go against these presumptions. The variance of count data typically outweighs the mean, leading to over-dispersion i.e E(yi)<var(yi). Given that the rate parameter is influenced by both a deterministic function and a random (unobserved) component, this may be the result of unobserved heterogeneity.

Excess zeros, which occur when observed zeros exceed those expected by the assumed distribution, may also contribute to the over-dispersion (Rose et al., 2006). Furthermore, over dispersion will lead to deflated parameter estimate standard errors and thus inflated t-statistics. As a result, after the construction of Poisson regression, a test of excessive dispersion must always be performed.otherwise when E(yi)>var(yi), we say that under-dispersion. Then, we used two tests of over dispersion, pitting the Null Hypothesis (H0), that the response variable mean and variance are equal against the Alternative Hypothesis (H1), that variance exceeds the mean,. Two fundamental criteria are frequently applied to determine whether over dispersion is present:

1. Deviance, $D(y,\hat{\mu})$ is given by

$$D(y,\hat{\mu}) = 2 * \sum\{y_i \ln(\frac{y_i}{\hat{\mu}_i}) - (y_i - \hat{\mu}_i)\}$$

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

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

$$X^2 = \sum(\frac{(y_i - \overline{\mu_i})^2}{\overline{\mu}})$$

Higher zero count rates and subject heterogeneity may contribute to over-dispersion. Deviance and Pearson Chi-square statistics divided by the degrees of freedom are roughly equal to one if the model matches the data. Values larger than one suggest an over-dispersion of the variance, whereas values less than one denote an under-dispersion. By adding a scale (dispersion) parameter to the connection between the variance and the mean, it is possible to account for over dispersion with regard to the Poisson model (Peden et al., 2001). Another method of determining whether there is over dispersion is to perform a statistical test of the hypothesis.

H0=$\alpha = 0$ Vs H1: $\alpha > 0$

If the P-value of LRTα < (level of significance), then there is overdispersion and the Negative Binomial model is preferred. The Negative Binomial Regression Model is more appropriate for over-dispersed data because it relaxes the constraints of equal mean and variance.

In the general, Poisson Regression Model, we think of $\mu_i$ as the expected desired number of children from the $i^{th}$ mother women and the total number live birth children from the $i^{th}$ the mother is Ni. This means, parameters will depend on the population size and the total number of live birth children from the individual mother. Thus, the distribution of Yi can be written as:

$$Yi \sim poisson(Ni\mu i)$$

where Ni are the total fertility rate of $i^{th}$ mother and $\mu_i = \exp(X_i{}^T \beta)$ The logarithm of the children of the children's birth lives is introduced in the regression model as an offset variable. By including

$$\log \mu_i = \log Ni + X_i{}^T \beta$$

The link between the expectation of the dependent variable and the linear predictor is a logarithmic function and the linear predictor contains a known part or offset. This allows for estimation of maximum likelihood, standard errors and the likelihood ratio goodness of fit chi-square statistics (Agresti, A. 2008). The model suggests that both sets of the parameters are dependent on the covariates.

Furthermore, the number of children born will be equal to the observed deaths if the coefficients of the independent variables, denoted by $\beta$ are all equal to zero. Since $\log N_i$ 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. The procedure therefore allows us to obtain the maximum likelihood regression coefficients that can be easily interpreted in terms of differentials in the dependent variables. Using the Negative Binomial Regression procedure, several regression equations are estimated to the relationship between under-five mortality changes when control variables earlier mentioned are introduced. Results from the Negative Binomial Models are sometimes better expressed on a more convenient scale.

### 3.4.2. Over dispersion Poisson model

A phenomenon known as over dispersion can be seen in data when the Poisson or binomial distributions are used to model the data. If the estimates of the dispersion after fitting, as indicated by the deviance or Pearson's chi-square, divided by the degree of freedom, are not near to one, the data may be under- or over-dispersed. If the estimations of the dispersion are less than or larger than one. It is usually defined the ratio of the variance $\delta$ 2 to the mean $\mu$, $D = \frac{\delta^2}{\mu}$ a measure to detect departures from the Poisson distribution.this yields the variance to mean ratio(D) is zero this means that the distribution is constant random variable or not dispersed , if D is greater than zero and less than one; binomial distribution with under distribution; If the dispersion ratio is close to one, a Poisson model fits well to the data i. e D = 1. when D is greater than one to occurs ove-rdispersion is occurs then the distribution is negative binomial distribution.

### 3.4.3. Negative Binomial regression model

The NB Regression Model is more flexible than the Poisson model and is used when count data are over dispersed (i.e when the variance exceeds the mean) (Hilbe, 2007; Hoffman, 2004). Overdispersion, caused by heterogeneity or an excess number of zeros (or both) to some degree is inherent to most Poisson data. By introducing a random component into the conditional mean, the Negative Binomial Regression Model addresses the issue of over-dispersion. However, it equally models both zero and nonzero counts, which might result in a poor fit for data with an excessive number of zeros. Therefore, it is always necessary to check the proportion of zero counts before developing a Negative Binomial Regression Model. This study used the likelihood ratio test to determine the more appropriate model between the

Poisson Regression and Negative Binomial Regression. Hilbe (2011) used the Negative Binomial Regression Model over dispersed Poisson data. When the Negative Binomial is used to model over-dispersed Poisson count data, the distribution can be thought of as an extension to the Poisson Model. The Negative Binomial Regression Model uses a log link function between the dependent variable(Ideal number of children of women) and independent variables.

In fact, the negative binomial regression model is in many ways equivalent to the Poisson regression model because the negative binomial model could be obtained from the mixture of Poisson and Gamma distribution called Poisson-Gamma distribution (Hilbe, 2011).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.

(Hilbe, 2011) used Negative Binomial Regression to Model over dispersed Poisson data. In the negative binomial regression model, a random term reflecting unexplained between-subject differences is included (Gardner et al., 1995), that is, the negative binomial regression adds an over dispersion parameter to estimate the possible deviation of the variance from the expected value under Poisson regression. Therefore, using the negative binomial regression to model count data with a Poisson distribution has the consequence of generating more conservative estimates of standard errors and may modify parameter estimates (Hilbe, 2011).

A random variable $y_i$ , i= 1, 2, 3 ……..is called a negative binomial distributed count with parameter λ and $\alpha$ the probability density function is expressed as follows

$$P(Y_i = y_{i,}\lambda_{i,}\alpha) = \frac{\tau(y_i + (\frac{1}{\alpha})}{\tau(\frac{1}{\alpha})y_i!}(1+\alpha\lambda_i)^{-1/\alpha}(1+\frac{1}{\alpha\lambda_i})^{-y_i}$$

-----------------------------------(3.2)

Where $Y_i>0$ and $\alpha>0$ with mean and variance are given by

$E(y_i)= \lambda_i\text{-}\exp(X^T\beta)$ and $var(y_i)= \lambda_i(1+ \alpha \lambda_i)$

Where, $\alpha$ shows the level of over-dispersion and Γ (.) is the gamma function.

If , $\alpha = 0$, NB Regression Model will reduce to Poisson Regression Model. This Model adds unobserved heterogeneity by specifying

$$E(y_i) = \lambda_i - \exp(X^T \beta)$$

$X_i^T$ is row 1*p vector of covariate (including an intercepts), p is the number of covariate Where, the model and px1 column vector of unknown regression parameters.

#### 3.4.3.1.Parameter estimation of NB model

The parameters of the negative binomial model are estimated by maximum likelihood approach by using numerical iterative algorithm commonly used is either Newton–Raphson or Fisher Scoring (McCullagh & Nelder, 1989). The likelihood function of the negative binomial model based on a sample of n independent observations is given by

$$l(y_{i,} \lambda_{i,} \alpha) = \prod_{i=1}^{n} \{ \frac{\tau(y_i + (\frac{1}{\alpha})}{\tau(\frac{1}{\alpha}) y_i !} (1 + \alpha\lambda_i)^{-1/\alpha} (1 + \frac{1}{\alpha\lambda_i})^{-y_i} \}$$

---------------------------------(3. 3)

The log-likelihood function ℓ of NB regression model is

$$l = \sum_{i-1}^{n} \{ -\log y_i ! + \sum_{k=1}^{n} (\alpha y_i - \alpha k + 1) - (y_i + 1/\alpha) \log(1 + \alpha\lambda_i) - y_i \log(\lambda_i) \}$$

Where $\frac{\tau(y_i + \frac{1}{\alpha})}{\tau(\frac{1}{\alpha}) y_i !} = \prod_{k=1}^{y_i} (yi + 1/\alpha - k) = \alpha^{-y_i} \prod_{k=1}^{yi} (\alpha yi - \alpha k + 1)$

For estimating regression coefficients β and dispersion parameter $\alpha$ The Newton-Raphson iteration procedure is applied like in the Poisson model.

## 3.5. Multilevel count regression analysis

### 3.5.1. The Reason for using Multilevel Model

The main reason to use multilevel model is specifically a multilevel count regression model, is justified for studying the determinants of fertility status among Ethiopian married women for several reasons. Some of them due to the hierarchical structure of the data, the presence of unobserved heterogeneity, the need to adjust for clustering effects, and the desire to analyze contextual factors that influence fertility outcomes. This due to the hierarchical structure of the data, the presence of unobserved heterogeneity, the need to adjust for clustering effects, and the desire to analyze contextual factors that influence fertility outcomes. This modeling technique offers a more thorough and precise understanding of the variables related to Ethiopian fertility status.

### 3.5.2. Multilevel models

Scholars such as Wong and Mason (1985), Langford (1990), Goldstein (1999), Bryk and Raudenbush (2004), and others have provided descriptions of the multilevel model. The multilevel structure of generalized multilevel models can be found in the generalized linear model of linear regression equation.multilevel/hierarchical modeling is persons nested inside groups (in this study, individuals nested within regions) and the clustering of the units of analysis are explicitly accounted. When dealing with multilevel data, it is used when the explanatory variable can be defined at any level while the dependent variable is at the lowest level. Regression analysis is the foundation of multilevel modeling (MLM), a technique for managing layered and clustered data.

A technique for analyzing data with complicated patterns of variability that focuses on layered reasons for variability is called multilevel analysis. The most appropriate method for analyzing multilevel data is to use a technique that, when used to refer to the units at higher levels of the nesting hierarchy, shows both within-group and between-group connections in a single study. It makes sense to visualize unexplained variation within groups and unexplained variation between groups as random variability by using probability models to describe the variability within and between groups. In a study including women within regions, for instance, unexplained variance within regions as well as variation between women is considered a random variable. Random coefficient models are a type of statistical model that can be used to analyze this kind of variance.

Variability in multilevel data, however, has a more complicated structure related to the fact that several population are involved in modeling such data ; one population for each Explaining variability in a multilevel structure can be achieved by explaining variability between level-1 units but also explaining variability between higher level units (Hox et al., 2017). These are employed in hierarchical data structures where basic units at level 1 are nested within level 2 clusters. which might then be stacked at level 3 in (super) clusters, and so forth.

Random effects, also known as latent variables, are perceived as unobserved heterogeneity at the difference levels that create dependence between all lower-level units that are a part of a higher-level unit. Random coefficients reflect variability in the relationship between the response and explanatory variables, while random intercepts reflect heterogeneity in the relationship between the response and explanatory variables. The optimal method for analyzing multilevel data is to use a single analysis that captures both within-group and between-group relationships, with "group" denoting the units in the upper levels of the nesting hierarchy (Hox et al., 2017).

Since the individuals in this study are nested regions, using a two-level count regression model makes sense. The regions are level-2, and the households are level-1. The multilevel regression model in this research is specifically indicated by the following notation.

Let Yij is represents the measure of the response variable Y with $i^{th}$ individual mother nested with the $j^{th}$ region i.e j=1,2,…N for higher level and i=1,2,…Nj individuals at group j. the level one model with explanatory variables $x1$,$x2$, - - -, $xp$, using logarithm transformation, can be written as:

$$\ln(\mu_{ij}) = \beta_{0j} + \sum_{p=1}^{k} \beta_{pj} X_{pij}$$ ------------------------------------------3. 11

where β0j is intercept parameters which are assumed to vary randomly across the regions and given by the sum of an average intercept $\beta_0$ and group dependent deviations (assumed mutually independent and normally distributed with mean zero and variance $\delta_0{}^2$). $\beta_{pj}$, p = 1,2, … , k ,are random slope parameters which are assumed to vary across the regions associated with the explanatory variables, Xpij. Xpij the level-1 variable (mother characteristics) differing from one to another in the same region, thus it has the intercept and the slope coefficients, so called random coefficients (Goldstein, 2011), written as:

$$\beta_{pj} = \gamma_p + \mu_{pj}, p = 0,1,2,...k$$ ------------------------------------3. 12

And $\mu_{pj}$ is the residual at level-two(region) with mean zero and variance $\delta^2{}_{\mu p}$.

For rally purpose let us to consider region-definite average number of children from individual mother, ln($\mu ij$), on a single level explanatory variable x. Therefore, we have two random components (intercept $\mu 0j$ and slope μ1 ) assumed to have a bivariate normal distribution N2 (0,Ω$\mu$), where the variance-covariance matrix is specified as:

$$\begin{bmatrix} \delta^2{}_{\mu 0} & \delta^2{}_{\mu 10} \\ \delta^2{}_{\mu 01} & \delta^2{}_{\mu 1} \end{bmatrix} \text{------------------------------------3. 13}$$

This model shows one independent variable which can be extended by including more variables that have random effects.

In a multilevel model the number of parameters is relatively large compared to a single model. Therefore, we need to limit the number of parameters that have their own importance based on our interest in theoretical problems. We need to start from a simple model, that is from a random intercept only model .

#### 3.5.2.1. Random Intercept –only Model

When examining the factors that influence the fertility status of married Ethiopian women, one can begin by examining the random intercept-only model, which is the most basic type of multilevel model. This model does not include any individual-level predictors; instead, it focuses on predicting the variation in fertility status across various clusters (e.g., communities or regions). The model makes the assumption that each individual inside a cluster has the same association between the reproductive status and the cluster-level component.

level l(individual level):

$$\ln(\mu ij) = \beta 0\text{j------------------------------------3. 14}$$

The coefficient $\beta 0j$ is called the level-2(region, cluster level) random coefficient we call this model is a random intercept. It can be rewritten as:

$$\beta_{0j} = \gamma_0 + \mu_{0j} \text{------------------------------------3. 15}$$

where $\gamma_0$ is fixed effect coefficient and $\mu 0j$ random term that is independently normally distributed with mean zero and variance $\delta^2{}_{\mu 0}$ (random intercept variance).then to substitute on the above equation to get:

$$\ln(\mu ij) = \gamma_0 + \mu_{0j} \text{------------------------------------3. 16}$$

It is also called the null model. The null model contains only the dependent variable and the intercept. Thus $\delta^2{}_{\mu 0}$ measures regional variations of the number of children.

### 3.5.3. The Full Random Intercept Model

The investigation of factors influencing fertility among married Ethiopian women may now include both individual- and cluster-level variables thanks to the complete random intercept model, which is an extension of the random intercept-only model. The impacts of both personas and contextual factors on fertility outcomes are captured by this model, which also takes into consideration the when the data's hierarchical structure.

The random part in this model is $\mu_{0j}$ which has a mean of zero and variance $\delta^2{}_{\mu 0}$.the full random intercept model is given by:

$$\ln(\mu ij) = \gamma_0 + \sum_{p=1}^{k} \gamma_p X_{pij} + \mu_{0j}$$ -----------------------------------3. 17

Ethiopian married women's reproductive status determinants can now be better understood thanks to the full random intercept model, which incorporates both individual- and cluster-level factors. While taking the clustering effect into account, it allows the estimate of the impacts of both contextual and individual features on reproductive outcomes.

The full random intercept model includes a larger range of predictors than the random intercept-only model, It provides a more sophisticated analysis. It offers a framework for investigating the interactions between cluster and individual level variables and how they affect married Ethiopian women's fertility.

### 3.5.4. The Random Coefficient Model

Not all regions would have the same relationship between the explanatory variables and the response. That is, the fertility status of women in different places may not be similarly influenced by the same explanatory variable. As a result, this model enables both the intercept and the slope parameters to change between regions and evaluates whether any of the explanatory variables has a large variance component between level-2 (regions). The model is provided by:

$$\ln(\mu_{ij}) = \gamma_0 + \sum_{p=1}^{k} \gamma_p X_{pij} + \sum_{p=1}^{k} \mu_{pj} X_{pij} + \mu_{0j}$$ -----------------------------------3. 18

The left hand side of this model in the above equation, $\gamma_0 + \sum \gamma_p X_{pij}$, is fixed part of the model because the coefficients are fixed whereas the remaining, $\sum_{p=1}^{k} \mu_{pj} X_{pij} + \mu_{0j}$ is called the random part. Testing random slope variation is best done on a one-by-one basis. Variables that cannot be included in the above equation may be included and analyzed here. Because for explanatory variables to have no significant mean regression slope but to have significant variance component for this slope.

### 3.5.5. Multilevel Poisson regression model

The log link function for the Poisson regression model with random coefficients is as follows, given the predicted number of living children for the women in the jth region, which is: $\ln(\mu ij) = \eta_{IJ} = X'_{IJ}\beta_J + \sum_{p=1}^{k} \mu_p X_{pij}$ ------------------------------------3. 19

If k is the number of parameters, or random coefficients, in the model, including the intercept, and p=0, 1, 2,... At level two, the coefficients are random (region). The probability distribution of the observed response is only defined by the level one individual randomness (Rasvash et al. 2009). A level one variable for the i th mother in the j th region, including the intercept, Xoij=1, is Xpij, p=0, 1, 2,... k. The vector ($\mu oj$, $\mu 1$, …, $\mu pj$) is considered to have a multivariate normal distribution with symmetric variance-covariance matrix and to be independently distributed with mean zero. The level two random effect's variance and covariance are indicated by:

$$Var(\mu_{pj}) = \delta^2{}_{\mu p},\ p = 0,1,2,...k$$
$$\text{cov}(\mu_{pj}, \mu_{sj}) = \delta_{\mu ps,},\ p = 0,1,...,k, and, p \neq s$$ ------------------------------------3. 20

The probability distribution of Yij is Poisson distribution so that the probability that Yij takes the specific value Yij is given by:.

$$p(Y_{ij} = y_{ij}) = \frac{\exp(\mu_{ij})\mu_{ij}{}^{yij}}{y_{ij}!}, y_{ij} = 0,1,2,$$ ------------------------------------3. 21

With the typical property that $E(Y_{ij}) = \text{var}(Y_{ij}) = \mu_{ij}$ which is the same as to $\exp(\eta_{ij})$ from the above equation. The exponential of each element relating to a single covariate, for each given region,exp$(\beta_p)$,of the predefined outcomes, Assuming all other covariates remain constant, vector $\beta$ provides the multiplicative effect on the mean number of occurrences $\mu_{ij}$ for a unit increase in the related covariate $X_{pij}$. In the event that the predictors are qualitative, they provide the multiplicative impact of belonging to the designated group in relation to the base.

The level-2 unpredictable element. The difference in $\mu ij$ between Regions is measured by $\Omega\mu$. The dispersion associated with the constant (intercept) of the model between Regions is provided by the first element in $\Omega\mu$, var ($\mu 0j$). If there are qualitative factors in the model, the intercept shows their combined effect on the reference category.

### 3.5.6. The Multilevel Negative Binomial regression Model

Equation of multilevel Poisson regression of the above is used to generate the multilevel negative binomial model by allowing for random variation between individuals in the expected number of events ($\mu ij$). The random variable $\mu ij*$ replaces the mean $\mu ij$ in the NB model:

$$\ln \mu_{ij}^{*} = \eta^{*}_{ij} + \varepsilon_{ij} \text{------------------------------------3. 22}$$

Where $\operatorname{cov}(\varepsilon_{ij}, \mu^{*}_{ij}) = 0$ and exp $(\varepsilon_{ij})$ follows gamma distribution with mean one and variance $\alpha = v^{-1}$, integrated with respect to residual(Colin & Pravin, 2013), the probability distribution given as

$$p(Y_{ij} = y_{ij}) = \frac{\exp(-\exp(\eta^{*}_{ij} + \varepsilon_{ij})\exp(\eta^{*}_{ij} + \varepsilon_{ij})^{yij})}{y_{ij}!} \text{------------------------------------3. 23}$$

We obtain the multilevel negative binomial model as seen below:

$$p(Y_{ij} = y_{ij}) = \frac{\Gamma(y_{ij} + v)v^{v} + \mu^{*}_{ij}{}^{yij})}{\Gamma(y_{ij} + 1)\Gamma(v)(v + \mu_{ij}^{*})^{v+yij}}, yij = 0,1,2,... \text{------------------------------------3. 24}$$

In this case, $E(Y_{ij} = y_{ij}) = \mu_{ij}^{*} = \exp(\eta^{*}_{ij})$. The variance, $\operatorname{var}(Y_{ij}) = \mu_{ij}^{*} + \alpha\eta^{*}_{ij})$, is different from the multilevel Poisson model, otherwise this is the same. Since the dispersion parameter in this case is α, the MLNB model's variance is greater than the MLP model's.

## 3.6. Estimation Techniques

The multilevel generalized linear model has a complicated statistical theory of parameter estimation. In almost every instance of generalized multilevel linear models, the covariance matrix of the random effects (or, in the case of a random-intercept model, the variance) and the fixed regression coefficients must be estimated. Maximum likelihood (ML), Marginal quasi-likelihood (MQL), Penalized quasi-likelihood (PQL), and Markov chain Monte Carlo (MCMC) are the most often utilized estimate techniques. Since the residuals in these models are non-linear in relation to the responses, a problem with them is estimating the residuals at higher model levels. The solution to this is to estimate the level-2 residuals using a first- or second-order Taylor series approximation.

In the case of generalized multilevel linear models, ML estimation is challenging because the Probability involves integrals that are not analytically solved. These are MQL and PQL. commonly used approximation techniques. The Taylor expansion is used by both MQL and PQL to reach the approximate result. Iterated Generalized Least Square (IGLS) can be used to fit them. RIGLS stands for limited iterated generalized least squares. Based on simulations, MQL typically tends to overestimate the variance parameters at the higher level. PQL estimation in second order is the most realistic estimate, but convergence issues are more likely to arise, especially if the model has one or more estimated huge residuals(Breslow & Clayton, 1993),(Christoffersen et al., 2023).

## 3.7. Comparison of the Models

There are different count regression models to be compared in order to select the appropriate fitted model, which fits the data well. This was done using likelihood-ratio test (LRT), Akaike information criteria (AIC), Deviance information criteria(DIC )and Bayesian information criteria (BIC). 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 [Dalrymple et al (2003) and Wang et al (1996)]. AIC is the most common means of identifying the model which fits well by comparing two or more than two models.

The comparison will start from the model without any independent variable with the model with adding the independent variable one by one through the full model. The model with the smallest value of AIC or of BIC is the preferable model to the dataset. 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 The formula is given as:

$$\begin{aligned} AIC &= -2\ell + 2K \\ BIC &= -2\ell + K\log(n) \end{aligned} \quad \text{-----------------------------------3. 25}$$

Where $\ell$ is the log-likelihood of a model that will compare with the other models, n is the sample size of the data and k is the number of parameters in the model including the intercept.

## 3.8. Goodness of fit tests

### 3.8.1. Likelihood Ratio test(LRT)

The likelihood-ratio test is used to assess the adequacy of two or more than two nested models. It compares the maximized log-likelihood value of the full model and reduced model. For instance, the null hypothesis can be stated as the over dispersion parameter is equal to zero (i.e. the Poisson model can be fitted well the data) versus the alternative hypothesis can be stated as the over dispersion parameter is different from zero (i.e. the data would be better fitted by the negative binomial regression).It is a test of a null hypothesis against an alternative 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:

$$LRT = G^2 = -2(l_{null} - l_k) \sim X^2{}_{p-1} \text{------------------------------------} 3.\ 26$$

Where: $\ell null$ is the log-likelihood of the null model and $\ell$k is the log-likelihood of the full model comprising k predictors, p is number of parameters and $x^2$ $(p-1)$ 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. In this study, to compare Poisson and NB regression models we used significance of dispersion parameter and likelihood ratio (LR) test as criterions. The statistic of likelihood ratio test for is given by the following equation:

$$LRT\alpha=-2(LL1-LL2)\text{------------------------------------}3.\ 27$$

This statistic has a Chi-squared distribution with 1 degrees of freedom and LL is log-likelihood. If the statistic is greater than the critical value then, model 2 is better than model one.

### 3.8.2. Vuong Test

The Vuong test is a non-nested test that is based on a comparison of the predicted probabilities of two models that do not nest (Vuong, 1989). That means vuong test statistics are needed to provide the appropriateness of zero-inflated models against the standard count models. This test is used for model comparison. For testing the relevance of using zero-inflated models versus Poisson and NB regression models, the Vuong statistic is used.

$$Mi = \log\left(\frac{P1(yi/xi)}{p2(yi/xi)}\right) \text{------------------------------------------}3.\ 28$$

Where , $p1(\frac{yi}{xi})$ and $p2(\frac{yi}{xi})$ are probability mass functions of zero-inflated and Poisson or NB models, respectively. In general, $PN(\frac{yi}{xi})$ is the predicted probability of observed count for case i from model N, then the Vuong test statistic is simply the average log-likelihood ratio suitably normalized. The test statistic is

$$v = \sqrt{n}\,\frac{\dfrac{\sum_{i=1}^{n} mi}{n}}{\sqrt{\dfrac{\sum (mi-\overline{m})^2}{n}}} = \frac{\sqrt{n}}{S_m}(\overline{m}) \text{------------------------------------3. 29}$$

Where, $\overline{m}$ are mean of mi, Sm standard deviation and n sample size

The hypotheses of the Vuong test are: Ho: E[mi] = 0 vs H1: E[mi] ≠ 0

The null hypothesis of the test is that the two models are equivalent. Vuong showed that asymptotically, it has a standard normal distribution (Vuong, 1989).

- ✔ □ If $V > \alpha/2$, the first model is preferred.
- ✔ If $V < \alpha/2$, the second model is preferred.
- ✔ If $|V| < \alpha/2$, none of the models are preferred

# 4. RESULT AND DISCUSSIONS

## 4.1. Statistical Data Analysis

In this chapter to examine the significant effect of the variables involved in the living number of children among women in Ethiopia. Important statistical software and programs were used for the analysis of the descriptive and inferential sections. Let's use the explanatory variables in this descriptive analysis to see the general summary of the data of the number of living children.

### 4.1.1. Number of living children per mother

Table 4.1 provided information on the number of living children, together with their frequency and percentage, in the sample who were fertile in a previous life before the survey was conducted. 0.80% of the study's female participants had more than ten living children. There are some women with no living children. 68.04% of mothers have children under the age of four. Most of the study's participants had one to four children, most of whom lived to see the study through to its completion.

**Table 4.1: frequency distribution of number of children with number of women**

| Number of living children women have | Frequency | Percent(%) |
|---|---|---|
| 0 | 3113 | 35.0 |
| 1 | 1204 | 13.6 |
| 2 | 1115 | 12.5 |
| 3 | 841 | 9.5 |
| 4 | 804 | 9.0 |
| 5 | 644 | 7.2 |
| 6 | 515 | 5.8 |
| 7 | 331 | 3.7 |
| 8 | 189 | 2.1 |
| 9 | 68 | .8 |
| 10+ | 61 | 0.6 |
| Total | 8885 | 100.0 |

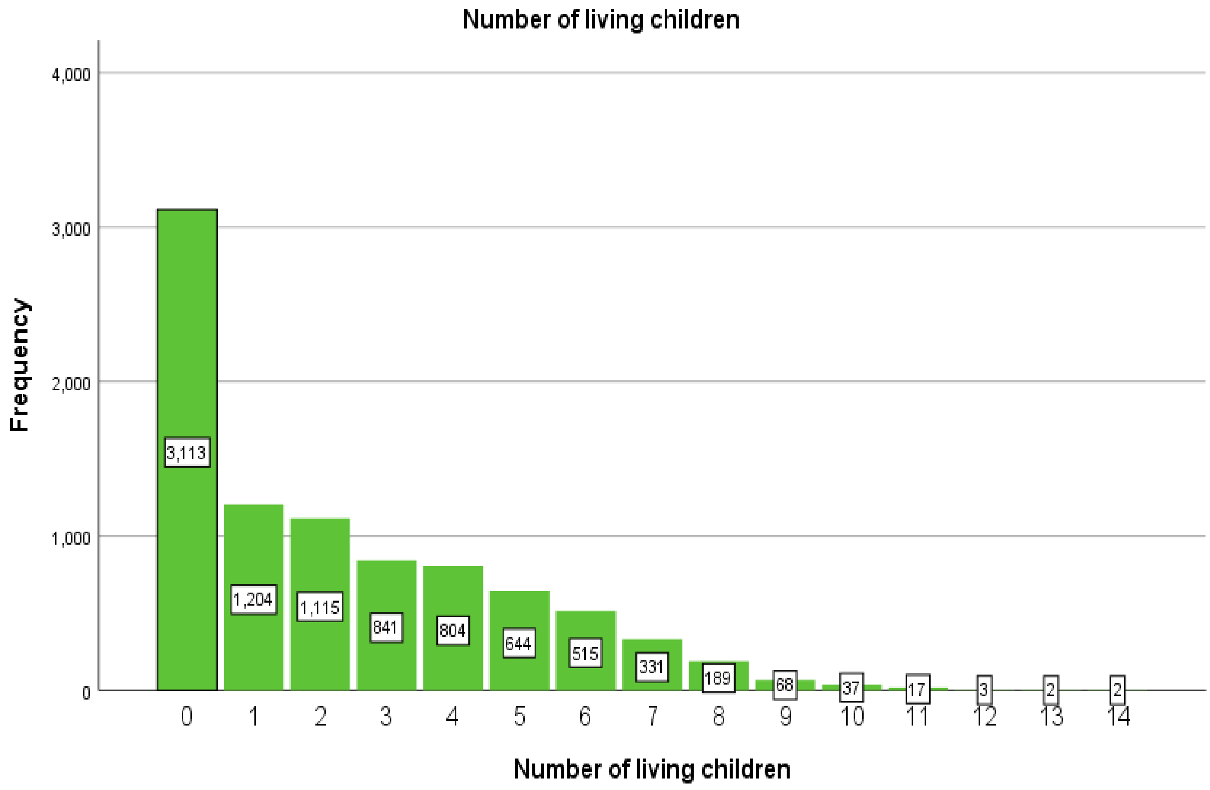



**Figure 4.1:Bar Graph of the number of women characterized by the number of children**

The bar graph demonstrated that a mother's pattern of living children was skewed to the right. The majority of the women (5772, or 65%) had children. among this (68.04%), had less than four children over their lifetime.

### 4.1.2. Summary statistics for predictor Variables

Demographic, socioeconomic and environmental related factors to the number of living children per mother are summarized in Table 4.2. The table Contains information on the average number of living children per woman by region; out of all region Somalia (3.05) and SNNP (2.79) had the largest mean number of living children per mother, while Addiss Abeba (0.95) had the lowest mean number of living children. Regardless of residential place, rural areas had a higher mean number of living children per mother (2.72) than urban areas (1.51).

Table 4.2: showed that the mean number of living children per mother for the Rich was 1.83, while the mean number of living children per mother for the Poor and Middle income levels was 2.95 and 2.41, respectively. The mean number of living children per mother who uses

contraception is 2.76, which is larger than the number of living children per mother who does not use contraception (2.18), according to the results.

The result also indicated that number of living children per mother in the current age group of women was 45-49 have highest mean number of children (5.12) as compared to mothers who had the lowest age group Similarly, mothers who was traditional religion have highest mean number of living children per mother (3.27) as compared to mothers who had on other religion follower. From the result can also observe that the highest mean number of living children per mother occurred with a marital status of the women who were married (3.26) as compared to unmarried women .

**Table 4.2: Summary statistics of predictor variables related to number of living children in Ethiopia**

| Respondents current age | Number living children | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10+ | mean | std |
| 15-19 | 1,869 | 188 | 38 | 4 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | .133 | .411 |
| 20-24 | 733 | 445 | 267 | 90 | 34 | 9 | 0 | 0 | 0 | 0 | 0 | .906 | 1.07 |
| 25-29 | 312 | 318 | 418 | 305 | 207 | 110 | 58 | 21 | 1 | 1 | 1 | 2.27 | 1.72 |
| 30-34 | 88 | 107 | 177 | 194 | 206 | 181 | 115 | 65 | 22 | 10 | 1 | 3.60 | 2.06 |
| 35-39 | 61 | 71 | 127 | 123 | 184 | 159 | 142 | 82 | 54 | 21 | 13 | 4.25 | 2.33 |
| 40-44 | 30 | 48 | 42 | 71 | 103 | 105 | 117 | 96 | 64 | 26 | 12 | 4.95 | 2.43 |
| 45-49 | 20 | 27 | 46 | 54 | 69 | 80 | 83 | 67 | 48 | 10 | 34 | 5.12 | 2.60 |
| Region | | | | | | | | | | | | | |
| Tigray | 235 | 120 | 91 | 71 | 70 | 64 | 40 | 20 | 17 | 4 | 1 | 2.29 | 2.32 |
| Afar | 150 | 94 | 101 | 77 | 69 | 48 | 43 | 34 | 11 | 9 | 3 | 2.75 | 2.45 |
| Amhara | 310 | 135 | 119 | 94 | 107 | 76 | 49 | 35 | 16 | 4 | 1 | 2.32 | 2.33 |
| Oromia | 351 | 117 | 123 | 75 | 103 | 85 | 72 | 55 | 40 | 15 | 8 | 2.73 | 2.79 |
| Somali | 218 | 41 | 55 | 59 | 54 | 58 | 58 | 49 | 24 | 12 | 9 | 3.05 | 2.94 |
| Benishangul | 232 | 102 | 82 | 74 | 88 | 63 | 51 | 30 | 17 | 3 | 4 | 2.52 | 2.45 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SNNPR | 321 | 87 | 112 | 103 | 102 | 98 | 87 | 49 | 28 | 11 | 6 | 2.79 | 2.64 |
| Gambela | 207 | 121 | 92 | 86 | 78 | 59 | 56 | 15 | 8 | 1 | 0 | 2.33 | 2.17 |
| Harari | 292 | 111 | 113 | 79 | 60 | 40 | 31 | 19 | 11 | 3 | 2 | 1.95 | 2.24 |
| Addis Ad | 448 | 142 | 120 | 65 | 23 | 13 | 4 | 2 | 1 | 0 | 0 | .95 | 1.3 |
| Dire Dawa | 349 | 134 | 107 | 58 | 50 | 40 | 6 | 24 | 23 | 16 | 6 | 0.92 | 1.2 |
| Place of Residence | | | | | | | | | | | | | |
| Urban | 1,323 | 512 | 438 | 261 | 157 | 99 | 59 | 52 | 32 | 11 | 7 | 1.51 | 1.96 |
| Rural | 1,790 | 692 | 677 | 580 | 647 | 545 | 456 | 279 | 157 | 57 | 54 | 2.72 | 2.58 |
| Religion | | | | | | | | | | | | | |
| Orthodo | 1,331 | 540 | 431 | 315 | 271 | 197 | 148 | 81 | 43 | 11 | 6 | 1.89 | 2.17 |
| Catholic | 26 | 12 | 9 | 6 | 10 | 5 | 8 | 2 | 0 | 0 | 0 | 2.24 | 2.22 |
| Protestan | 560 | 210 | 229 | 159 | 163 | 142 | 115 | 64 | 44 | 15 | 10 | 2.47 | 2.50 |
| Muslim | 1,173 | 438 | 435 | 350 | 346 | 289 | 238 | 183 | 99 | 41 | 43 | 2.62 | 2.64 |
| Tradition | 16 | 2 | 7 | 7 | 10 | 7 | 5 | 1 | 2 | 1 | 2 | 3.27 | 2.81 |
| Other | 7 | 2 | 4 | 4 | 4 | 4 | 1 | 0 | 1 | 0 | 0 | 2.67 | 2.20 |
| Sex of Household | | | | | | | | | | | | | |
| Male | 2,082 | 801 | 828 | 630 | 619 | 499 | 399 | 264 | 151 | 57 | 50 | 2.48 | 2.51 |
| Female | 1,031 | 403 | 287 | 211 | 185 | 145 | 116 | 67 | 38 | 11 | 11 | 1.90 | 2.28 |
| Wealth index | | | | | | | | | | | | | |
| poor | 864 | 322 | 363 | 314 | 349 | 324 | 276 | 165 | 104 | 35 | 32 | 2.95 | 2.64 |
| middle | 436 | 182 | 163 | 138 | 134 | 110 | 85 | 60 | 19 | 10 | 5 | 2.41 | 2.40 |
| riche | 1,813 | 700 | 589 | 389 | 321 | 210 | 154 | 106 | 66 | 23 | 24 | 1.83 | 2.23 |
| Contraceptive use | | | | | | | | | | | | | |
| No | 2,875 | 733 | 674 | 553 | 549 | 471 | 388 | 268 | 155 | 52 | 50 | 2.18 | 2.54 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Yes | 238 | 471 | 441 | 288 | 255 | 173 | 127 | 63 | 34 | 16 | 11 | 2.76 | 2.12 |
| Marital status | | | | | | | | | | | | | |
| Unmarri | 2,242 | 40 | 7 | 2 | 2 | 3 | 3 | 1 | 0 | 0 | 0 | 0.05 | .39 |
| Married | 648 | 922 | 952 | 727 | 715 | 578 | 469 | 304 | 173 | 65 | 36 | 3.26 | 2.40 |
| Other | 223 | 242 | 156 | 112 | 87 | 63 | 43 | 26 | 16 | 3 | 1 | 2.22 | 2.09 |
| Age at first birth | | | | | | | | | | | | | |
| <=15 | 223 | 125 | 203 | 233 | 269 | 249 | 213 | 144 | 83 | 38 | 32 | 3.97 | 2.56 |
| 16-19 | 1,399 | 459 | 434 | 332 | 313 | 233 | 182 | 135 | 75 | 20 | 19 | 2.15 | 2.41 |
| =>20 | 1,491 | 620 | 478 | 276 | 222 | 162 | 120 | 52 | 31 | 10 | 10 | 1.62 | 2.03 |

In the Appendix :Contains information on the average number of living children per woman by region. There was regional variance in the mean number of children a mother experienced during her childbearing age, as shown in figure A4 appendix A. Out of all the regions, Addis Ababa had the lowest mean number of children per mother, while the Somalia region had the highest mean number of children per mother.

Summaries of the variables that are thought to influence mothers' fertility are shown in Table A1 Appendix . Regional summaries are provided for the chosen variables, which include place of residence ,Region, Religion, economic status, current contraceptive use, Sex of household heads, Marital status, age at first birth etc. The table shows that at regional level 33.21% of the women who are at the reproductive age group(15-49) in the study were living in urban areas while other women are living in rural areas. There is a higher variation in place of residence among the reproductive age group when the women that live in rural areas are twice as much as urban. This implies that fertility is higher among rural women than it is among urban women.

From the result, the wealth index of women in the study at a low economic level (poor) is 3148(35.43%) and 1342(15.10%) are medium while the others are rich. There is a higher variation in the economic level of women households in Addis Ababa which is 0.08% was poor, 6.60% were medium and 92.54% were rich. Afar (5.64%) and Somalia (5.83%) were the poor, whileAmehara(3.22%), Benishangul(3.88%) SNNP(3.92%)& Gambela(3.69%)

were almost the same economic status which is also the poor women found in this region. In addition to this , 49.47% were rich mothers, 35.43% were poor and 15.10 were of medium economic status.

71.81% of household heads were male and the remainder were female household heads nationally. Regionally in Oromia there were higher respondents whose household head was male(88.12%), while in Somalia the lowest (51.56%) were male. even among female respondents whose household heads were highest(48.44%) in the Somalia region.

It is shown that at the regional level, the marital status of the women in the survey 25.89 were unmarried mothers and 63.17% were married while the remain is others' were 10.94% in regional level

Majority of women in the survey (76.17%) respondents were not using contraceptive. From Table A1.Regionally in Somalia region (97.7%) were not using contraceptive higher number of respondents were no using contraceptive among the respondents. In Amhara region there was higher user of contraceptive as compared to the other regions.

Among the respondents of women the Muslim women (40.91%) was higher than the other religion type, there is a higher variation in Religion of women household in afar 90.50% and Somalia (97.66%) were Muslim respectively. In addition to this there were no catholic and protestant(0.00%) women in the Somalia region.

## 4.2. Single level analysis

### 4.2.1. Factors of fertility and variable selection methods

In order to select the best variable to include in multivariate analysis, stepwise variable selection method was used. The result recognized that predictors with respect to the p-value; less than 0.25 at the time of univariate analysis; in the process wealth index, respondent's current age, Region, place of residence, highest education level, religion, contraception use or not, Marital status ,current age group, sex of household head, age of household head and age at first birth had been checked and statistically significant variable. Hence these significant variables are considered in the multivariable count regression models.

#### 4.2.2. Determinants of fertility and Model selection criteria

Poisson regression and the negative binomial regression model were fitted in order to determine the determining factors of reproductive aged women's fertility status in Ethiopia. The model that best fit the available fertility data was chosen. To check for over- or under-dispersion, the dispersion parameter was examined. Underdispersion, on the other hand, is extremely uncommon in real-world data problems, whereas overdispersion is more typical (Germán Rodrúguez, 2013). The Poisson Regression model better fit than the Negative regression model if the dispersion parameter is substantial and exhibiting overdispersion, and vice versa.

### 4.2.3. Goodness of fit test and Information Criteria

This is one way of checking dispersion parameter. The ratio of the Pearson Chi-square and Deviance statistics to the corresponding degrees of freedom, as shown in Table 4.3, is close to one. However, since both give a result that seems a good fit, I need to check whether the dispersion parameter is significant or not in addition to AIC and BIC values. To determine the importance of the dispersion parameter, a formal statistical test of the dispersion parameter $\alpha$ was performed. The dispersion test can be expressed as follows:

H0: $\alpha = 0$ (no overdispersion) vs.

H1: $\alpha \neq 0$ (dispersion exists).

According to the probability ratio chi square statistic with one degree of freedom; no over dispersion (P-Value< 0.05) It suggests that the data are not dispersed, and the Poisson model is better than the other model**.**

**Table 4.3: Test for overdispersion in the model**

| Test statistics | Value | Degrees of freedom | Value/DF |
|---|---|---|---|
| Deviance goodness-of-fit | 6082.235 | 8853 | 0.697 |
| Pearson goodness-of-fit | 6418.937 | 8853 | 0.725 |

Another way of comparing model fit is by the AIC or BIC values. In order to select the best model which fits the data well, different models were considered. In this study, different model selection criteria were considered like the log-likelihood, AIC and BIC in order to identify the most fitted model. From Table 4.4 the results of the two models suggested that the poisson regression model is better fits than the negative binomial regression model since it has small AIC value.

From Table 4.4: result, to conclude that the Poisson model fits reasonably well because the goodness-of-fit chi-squared test is statistically significant (deviance goodness of fit test at 8853 degree of freedom the Pearson goodness of fit test at 8853 D.F. (see table 4.3 in the above). The null hypothesis is accepted or the Poisson model is sufficient at the specified significance level of (5%), as indicated by the non-significant result. Therefore, the analysis discussed in the subsequent section is based on the Poisson regression model.

Poisson model is more appropriate than the other count models to fit the number of living children per mother. Due to the fact that it has a lower AIC (24248.59) and BIC ( 24251.05) value.

**Table 4.4: Model selection criteria for the count regression models**

| Model | Obs | Df | AIC | BIC |
|---|---|---|---|---|
| poisson | 8885 | 101 | 24248.59 | 24251.05 |
| NB | 8885 | 102 | 24964.89 | 24974.45 |

### 4.2.4. Likelihood Ratio Test (LRT)

The result from Table 4.5. indicates that p-value is greater than $\alpha$-value it implies that Poisson is better than the NB model. The AIC, BIC and log likelihood also supported the Poisson model from the NB count model.

**Table 4.5: Likelihood Ratio Test**

| Criteria | Model | LRT test statistics(p-value) | Preferable model |
|---|---|---|---|
| LRT | poisson versus NB | 0.6279 | Poisson |

## 4.3. Results of the Poisson regression Analysis

The determining factors and regional variation of fertility were analyzed using the Poisson Regression Model. Therefore, the Poisson analysis, both simple and multiple, was used. We must introduce the variables into the model at various phases in order to determine how they each contribute to fertility. One method for choosing variables is to fit a model, starting with a straightforward model that only has the intercept term. We can then add explanatory variables to each subsequent model, and we are able to assess the significance of these additions by comparing the fitted log likelihoods or deviances between the models.

Consequently, starting with univariable analysis, four steps were utilized to incorporate all variables in the final model appropriately. The mothers' residence at the time of the survey is the only location in which the variable Region is included in the first model (Model I). Thus, this model helps in observing variations in fertility by Region. The second model is an extension of the first model by adding some socioeconomic variables, such as economic status (wealth index), place of residence, current use of contraceptives, religion, and marital status.

Model III is an expansion of Model I, including demographic characteristics such as the sex of the head of the household, the age of the mother at her first birth, the mother's current age, and the age of the household head . Lastly, all of the variables from the previous models are included in the final model (model IV), which makes it possible to observe how the predictors together affect fertility.

Deviance goodness of fit test was used to evaluate the goodness-of-fit test for the fitted poisson model (model I–IV). All of them could fit the data at the 5% level of significance (P-value<0.05), but the most reliable model was determined by employing a deviance-based test to identify the model with the greatest improvement. Consequently, at the 5% level of significance, it is possible to state that at least one of the coefficients ($\beta i$) in each model differs from zero. The inclusion of explanatory factors was used to perform the model comparison deviance test.

As a result, model II's deviation test against model I demonstrates that model II enhanced the fit of the information as a result of the inclusion of socioeconomic factors ($\chi 2$ = 6985.3 – 456.02 = 6529.28 with P-value for 1 degree of freedom <0.0001). In a similar manner, model III and I, model IV and I, model IV and II, model IV and III and model II and III were compared having chi-square values 9255.15, 12463.48, 5934, 3208.33and 2725.87 with P-value<0.0001, respectively. In comparison to the previous models, model IV fits the data better because it showed the greatest reduction in deviation. The information criteria (AIC) and BIC can be viewed in addition to the deviance-based goodness of fit test. Model four fits the data better than the other three models and has smaller AIC and BIC values. The final model mode (IV) serves as the basis for the interpretation that follows.

The result in Table 4.6 showed the existence of regional variation in fertility status of women in Ethiopia. The fertility of mothers in Afar region was decline with approximate value of 0.877times lower as compared to the reference group of Tigray in fertility keeping other factors remain constant with an interval of (C.I: -0.211 -0.051, P-value<0.05). Fertility in Oromia region was declines as compared to the reference region of Tigray with approximately value of 0.942 times lower than that of the reference region (C.I: -0.130,0 .009, P-value<0.05). Fertility of age reproductive in Somali Region is 1.093 times higher as compared toTigray. 9% higher possibility of fertility was seen in Somali Regional state compared to the reference category with (C.I:0.010 ,0.169, p value,0.05). This Region shows the highest fertility per mother compared to the reference group(See Table 4.6).The model also shows that the chance of women fertility in Addis Ababa is 0.751 times lower as compared to Tigray i.e lower possibility of fertility was seen in Addis Ababa administrative city compared to reference category of Tigray (C.I: 1.101 1.31, p-value).

Model IV also shows the other home level characteristics of mothers' fertility. From the point of view of the effect of place of Residence, married women in the rural area have 1.220 times more chance of high fertility as compared to Urban Women with confidence intervals of (C.I: 0.159 0.239, p-value 0.05).

The economic status or wealth index of a household is also found to affect fertility of women significantly. The result indicated women in medium wealth index were found to be more likely to have lower mean number of living children (0.90) as compared to poor wealth index (C.I: -0.145 -.061) The same is true for rich economic level of wealth index of household of women in the child bearing age as compared to poor households (0.825, See below Table 4.6).

Another important determinant factor of Ethiopian women is use of contraceptives. As indicated in Table 4.6, women who are using contraceptives are less likely to have mean number of living children as compared to those who use contraceptives. Women who are not using contraceptives are 1.055 times more likely to have a higher mean number of living children (C.I: 0.0213, 0.087). Therefore using contraceptives is an important predictor variable determining the fertility of women in Ethiopia even though the difference is not that much surprising.

In addition to this, women's current age and women's age at first birth were found to be other important variables on the number of children a woman has. Women whose age at first birth was in between 16-19 were less likely (0.824) to have more number of living children than that of a woman aged at first birth 15 years and below (C.I: -0.226 -0.161) The same is true for those women whose age at first birth is 20 years and above as compared to the reference category (59% decline).

**Table 4.6: Poisson Regression models for fertility status of women**

| | Predictor variable | Models | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | ModelI | | | ModelII | | | ModelIII | | | ModelIV | | |
| | | β | SE(β) | Exp(β) | β | SE(β) | Exp(β) | β | SE(β) | Exp(β) | β | SE(β) | Exp(β) |
| **Region** | Tigray(Ref) | | | | | | | | | | | | |
| | Afar | 0.182 | 0.063 | 1.199 | -0.266* | 0.054 | 0.766 | 0.249* | 0.040 | 1.283 | -0.131 | 0.041 | 0.877 |
| | Amhara | 0.013 | 0.058 | 1.013 | -0.084 | 0.043 | 0.919 | -0.162* | 0.037 | 0.850 | -0.188 | 0.033 | 0.830 |
| | Oromiyaa | 0.176 | 0.056 | 1.192 | 0.002 | 0.047 | 1.002 | 0.074* | 0.036 | 1.077 | -0.060 | 0.035 | 0.942 |
| | Somalia | 0.288 | 0.062 | 1.334 | -0.051 | 0.054 | 0.950 | 0.446* | 0.038 | 1.562 | 0.089 | 0.041 | 1.093 |
| | Benishang | 0.098 | 0.061 | 1.103 | -0.121* | 0.048 | 0.886 | 0.009 | 0.039 | 1.001 | -0.144 | 0.036 | 0.866 |
| | SNNP | 0.198 | 0.056 | 1.219 | 0.034 | 0.049 | 1.035 | 0.025 | 0.036 | 1.025 | -0.086 | 0.036 | 0.918 |
| | Gambela | 0.018 | 0.062 | 1.018 | -0.170* | 0.052 | 0.844 | -0.033 | 0.040 | 0.967 | -0.184 | 0.039 | 0.832 |
| | Hareri | -0.156 | 0.062 | 0.855 | -0.135* | 0.054 | 0.874 | -0.095* | 0.040 | 0.909 | -0.103 | 0.041 | 0.902 |
| | Dire Dawa | -0.239 | 0.061 | 0.787 | -0.101* | 0.048 | 0.904 | -0.144* | 0.040 | 0.866 | -0.145 | 0.041 | 0.865 |
| | Addis A. | -0.875 | 0.066 | 0.417 | -0.228* | 0.053 | 0.796 | -0.542* | 0.048 | 0.582 | -0.287 | 0.048 | 0.751 |
| | Intercept | 0.828 | 0.043 | 2.289 | | | | | | | | | |
| Resid | Urban(Ref) | | | | | | | | | | | | |
| | Rural | | | | 0.221* | 0.026 | 1.247 | | | | 0.199 | 0.020 | 1.220 |
| Wealt | Poor(Ref) | | | | | | | | | | | | |
| | Middle | | | | -0.138* | 0.029 | 0.871 | | | | -0.103 | 0.021 | 0.902 |
| | Rich | | | | -0.207* | 0.023 | 0.813 | | | | -0.192 | 0.017 | 0.825 |
| contra | yes use(Ref) | | | | | | | | | | | | |
| | No | | | | -0.093* | 0.022 | 0.911 | | | | 0.054 | 0.017 | 1.055 |
| Religion | Ortodox(Ref) | | | | | | | | | | | | |
| | Catolic | | | | 0.157 | 0.106 | 1.169 | | | | 0.054 | 0.079 | 1.055 |
| | Protestant | | | | 0.116 | 0.034 | 1.123 | | | | 0.125 | 0.026 | 1.133 |
| | Muslim | | | | 0.158 | 0.030 | 1.171 | | | | 0.188 | 0.023 | 1.207 |
| | Traditional | | | | 0.130 | 0.104 | 1.139 | | | | 0.065 | 0.075 | 1.067 |
| | Other | | | | 0.186 | 0.163 | 1.204 | | | | 0.167 | 0.120 | 1.182 |
| Marital status | Unmarried(Ref) | | | | | | | | | | | | |
| | Married | | | | 4.181* | 0.098 | 65.431 | | | | 2.791 | 0.100 | 16.297 |
| | Other | | | | 3.864* | 0.105 | 47.655 | | | | 2.462 | 0.102 | 11.728 |
| Age of | 15-19yrs(Ref) | | | | | | | | | | | | |
| | 20-24 | | | | | | | 1.849 | 0.066 | 6.353 | 1.117 | 0.066 | 3.056 |
| | 25-29 | | | | | | | 2.762 | 0.062 | 15.831 | 1.815 | 0.063 | 6.141 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 30-34 | | | | | | | 3.231 | 0.062 | 25.305 | 2.202 | 0.063 | 9.043 |
| | 35-39 | | | | | | | 3.468 | 0.062 | 32.073 | 2.411 | 0.063 | 11.145 |
| | 40-44 | | | | | | | 3.648 | 0.624 | 38.398 | 2.548 | 0.064 | 12.782 |
| | 45-49 | | | | | | | 3.800 | 0.634 | 44.70 | 2.677 | 0.065 | 14.54 |
| Se | Male(Ref) | | | | | | | | | | | | |
| | Femal | | | | | | | -0.316 | 0.017 | 0.729 | -0.041 | 0.021 | 0.960 |
| Age of HH. | | | | | | | | -0.010 | 0.001 | 0.990 | -0.002 | 0.001 | 0.998 |
| Age | <=15yrs | | | | | | | | | | | | |
| | 16-19 | | | | | | | -0.280* | 0.020 | 0.756 | -0.194 | 0.017 | 0.824 |
| | >=20 | | | | | | | -0.660* | 0.021 | 0.517 | -0.532 | 0.018 | 0.587 |
| Deviance | | 456.02 | | | 6985.3 | | | 9711.17 | | | 12919.50 | | |
| AIC | | 35632.47 | | | 29105.19 | | | 26375.31 | | | 23206.98 | | |
| BIC | | 35717.57 | | | 29197.39 | | | 26453.33 | | | 23426.84 | | |
| DF | | 10 | | | 11 | | | 9 | | | 29 | | |

## 4.4. The Multilevel Poisson Regression Analysis

There is a variation in the number of children of a mother among different regions, which was conducted by the multilevel analysis. The main difference between the multilevel and single level analyses in this case is that the first type of analysis only indicates the existence of regional variation among regions, whereas the latter allows us to potentially identify the magnitude of regional variation in women's fertility as well as the existence of variation among factors between regions. To perform the formal multilevel model, an explanatory analysis (Graphical) was performed on the data. As a result, we must construct a model with specific parameters for every location. This could be carried out to observe how different explanatory variables have an impact in each region. To see how they vary by region, the covariates with the biggest difference on the graph can be analyzed in a random effect. Similarly, the slope of each region can be examined with a chosen variable. To put it simply, the two or three significant factors with the most variations can be considered as major predictors of the variation in mothers' fertility across the various locations.

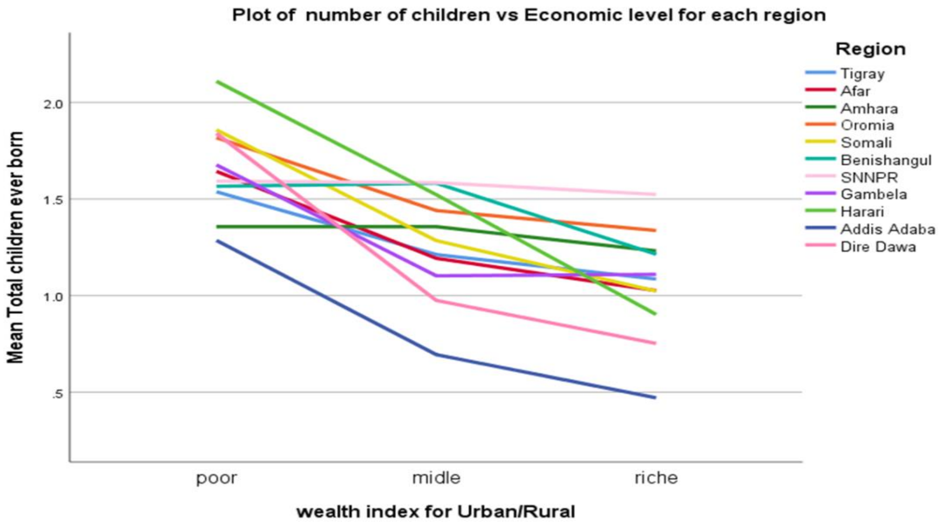



**Figure 4.2: plot 0f Number of living children vs economic level for each region**

Figure 4.2 shows the plot of the designated predictor, economic status against the expected value of the total number of children born in all locations. Economic status of a women household is measured using the wealth index. This is how a multilevel structure for a given variable can be visually investigated. This graph shows how, depending on the region, women's fertility is influenced differently by their economic condition. This graph illustrates how economic status affects women's fertility differently in different regions. A closer examination of figure 4.2 shows that fertility rises in proportion to economic status. However, when economic status rises in the SNNP region, the fertility rate remains constant. Fertility varies from region to region, which is a significant difference between them.

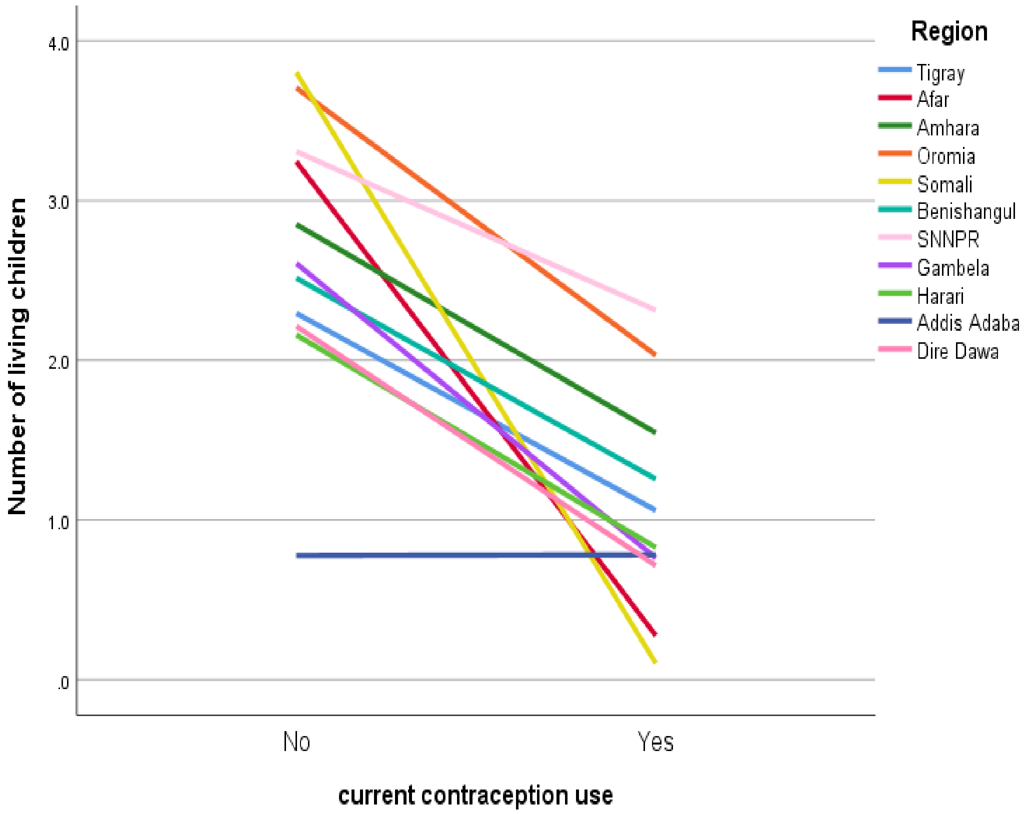



**Figure 4.3: Plot of Number of living children vs mother's contraceptive use for each region**

The contraceptive use of women's households is shown in the figure 4.3, fertility and mother's contraceptive use have no direct relationship among regions. In the majority of the regions fertility is high when not using contraceptive methods, but not in all. So the graph indicates that there is slight variation among regions between fertility and contraceptive use, while the fertility and contraceptive use in Addis Ababa is the constant number of fertility between using and not. The plots of other covariates are shown in Appendix B. Thus the covariates showing the highest variation on fertility among regions compared to other covariates can take its coefficient as random in the model.

The deviance based chi-square test, the empty model; the random intercept model and the random coefficient model have been used in the multilevel Poisson regression analysis. The AIC and BIC values can be applied for model comparison analysis. The random coefficient model was the first model compared, starting with the single level empty model. As a result, the random intercept model with smaller AIC and a deviance-based chi-square test ($X^2$ = 23250.62., P −value < 0.0000) which is better fits to the data. The comparison between the random intercept, random coefficient, and empty models are shown in Table 4.7. The model shows that of them, the random intercept model has smaller AIC values across alternatives and fits the data more well when tested using the deviance based chi-square test was candidates.

**Table 4.7:Summary for Multilevel Poisson Regression Model selection criteria based on deviance chi-square test statistics**

| | | Empty model | Random intercept | Random coefficient |
|---|---|---|---|---|
| | Log likelihood | -20686.3 | -11625.31 | -19051.97 |
| Model selection criteria | Deviance $X^2$ test | 41372.6 | 23250.62 | 38103.94 |
| | p-value | 0.0000 | 0.0000 | 0.001 |
| Model fit Diagnosis | AIC | 41378.6 | 23296.63 | 38135.54 |
| | BIC | 41399.87 | 23459.75 | 38249.42 |

Significance at 5%

### 4.4.1. Random intercept only model

To see the variation caused by regional effects, we must first take into account the random intercept only model. According to the results of the random intercept only model, there is a significant random variation between the regions (P − value < 0.05, $\hat{\sigma}2\mu0$ = 0.1003). Since the logarithmic function serves as the link function between the linear predictor and the dependent variable's expectation, the constant term in Table 4.8 can be understood as the inverse of the logarithm of its value. In all studied regions, the average number of living children per mother is (4.354=exp (1.471)).

**Table 4.8: the multilevel Poisson random intercept only model**

| Fixed effect | estimate | SE | Exp($\beta$) | P-value |
|---|---|---|---|---|
| $\beta_0$(constant) | 1.471 | 0.278 | 4.354 | 0.000 |
| Random effect | | | | |
| Random intercept variance ($\widehat{\delta^2 0\mu}$) | 0.220 | 0.1003 | | 0.0000 |
| Deviance based chi-square | 832.34 | | | <0.00001 |
| AIC | 41378.6 | | | |
| BIC | 41399.87 | | | |

### 4.4.2. Random Intercept and fixed coefficient Poisson Regression Model

The most important task in a multilevel model is to add the explanatory variables (predictors) as fixed effects and observe their impact on the response variable. Here, the explanatory factors remain as fixed effects or have similar effects across regions on the number of living children a mother has, allowing the random intercept in the model to vary across regions. Following the fitting of the Poisson multilevel model with random intercept and fixed coefficients; we can compare it to the random intercept only (empty) model.

Thus, compared to the random intercept only model ($\chi2$ = 23250.62), the random intercept model with fixed explanatory variable better fits the data than random intercept fixed coefficient model. Additionally, the random intercept model result indicates that the random intercept's level two or (region's) variance ($\sigma 20\mu$) is significant at the 5% level.

The result also shows us contraceptive use is one of the determinant factors of fertility in Ethiopia (See Table 4.9). When mother's contraceptive use , the number of children that would be born 1.05 times as compared to those who have no use of contraceptive other factors constant. The interpretations of other significant variables are similar.

At the 5% level of significance, the variation in mothers' fertility is significantly impacted by all fixed effect variables, with the exception of the variables corresponding to the household head's of age and sex. When the other variables are taken into account and the intercept parameter is allowed to vary among regions, the probability that a mother in a rural area would give birth to children is 1.22 times higher than in an urban area.

The random intercept model in the multilevel poisson model becomes larger than the variance of the random intercept model. This may be the result of the model's fixed-effect explanatory variable additions, which have their own independent predictive power predicting mother fertility all over regions.

**Table 4.9: Result of predicted Poisson multilevel model with random intercept for regression effects of mothers characteristics on fertility status**

| Fixed effects | | Estimate($\beta$) | St.error | Exp($\beta$) | P-value |
|---|---|---|---|---|---|
| Current age group | 20-24 | 1.105* | 0.066 | 3.020 | 0.000 |
| | 25-29 | 1.805* | 0.063 | 6.080 | 0.000 |
| | 30-34 | 2.184* | 0.063 | 8.882 | 0.000 |

| | | | | | |
|---|---|---|---|---|---|
| | 35-39 | 2.391* | 0.063 | 10.924 | 0.000 |
| | 40-44 | 2.530* | 0.064 | 12.553 | 0.000 |
| | 2.639 | 0.064* | 0.066 | 1.070 | 0.000 |
| Place of residence | Urban(Ref) | | | | |
| | Rural | 0.198 | 0.020 | 1.219 | 0.000 |
| Religion | Ortodox | | | | |
| | Catolica | 0.059 | 0.080 | 1.061 | 0.450 |
| | Protestant | 0.128 | 0.025 | 1.136 | 0.000* |
| | Muslim | 0.193 | 0.022 | 1.213 | 0.000* |
| | Traditional | 0.087 | 0.085 | 1.091 | 0.240 |
| | Other | 0.153 | 0.120 | 1.165 | 0.202 |
| Sex of household | Male(Ref) | | | | |
| | Female | -0.047 | 0.021 | 0.954 | 0.023* |
| Age of household | | -0.0020 | 0.001 | 0.998 | 0.007* |
| Economic status (wealth index) | Poor(Ref) | | | | |
| | Middle | -0.103 | 0.021 | 0.902 | 0.000* |
| | Rich | -0.196 | 0.017 | 0.822 | 0.000* |
| Current contraception use | Yes(Ref) | | | | |
| | No | 0.047 | 0.017 | 1.05 | 0.005* |
| Marital status | Unmarried(Ref) | | | | |
| | Married | 2.754 | 0.999 | 15.705 | 0.000* |
| | other | 2.44 | 0.101 | 11.473 | 0.000* |
| Age at first birth | <=15(Ref) | | | | |
| | 16-19 | -0.193 | 0.017 | 0.0.824 | 0.000* |
| | >=20 | -0.532 | 0.018 | 0.587 | 0.000* |
| Constant | cons($\beta_0$) | -3.464 | 0.117 | .03 | 0.000* |
| Random effect | | | | | |
| Varince($\delta^2_{0\mu}$) | | 0.009 | 0.004 | 1.009 | 0.0001* |
| Deviance chi-square | 23250.62 | | 0.000* | | |
| AIC | 28507.26 | | | | |
| BIC | 28627.83 | | | | |

Ref= reference categories,*Significance (P<0.05)

The predictor variables, mother's place of residences , economic statues, contraceptive use, sex of household head, age at first birth, Marital status and current age of mother's were found to be significant determinants in the variation of fertility of women among the regions with respect to the corresponding reference category (See Table 4.9). The variance of the random intercept ($\hat{\sigma}20\mu$=0.009) was found to be significant and indicates that the number of living children differs among regions with (CI:0.004, 0.026).

### 4.4.3. Random Coefficient Model

Understanding how the explanatory variables in the study affect the dependent variable differently depending on the region consequently, the multilevel model with a random intercept and slope is fitted for those showing highest variation between the regions. Using the graphical exploratory data analysis method, the variable showing the largest variation in maternal fertility between regions was selected as the random coefficient within the model. As a result the model has the variance and covariance terms of the appropriate random coefficient variables in common with the fixed effect coefficients and an overall level-two regional variance of constant term.

Age of a mother at first birth and Religion show the highest difference among regions and so that we are allowing them to vary across regions with others as fixed effect or having similar effect on fertility of women among regions. Table 4.10 contains the fixed effect coefficients, and an overall regional variance constant term ($\hat{\sigma}20\mu$) together with variance and covariance terms of the corresponding random coefficient variables. In this random coefficient model the religion and age at first birth are allowed to vary between regions.

**Table 4.10: Result of predictor fixed and Random coefficient model**

| Fixed effects | | Estimate | St.error | Exp($\beta$) | P-value |
|---|---|---|---|---|---|
| Current age group | 20-24 | 1.100* | 0.066 | 3.004 | 0.000 |
| | 25-29 | 1.800* | 0.063 | 6.05 | 0.000 |
| | 30-34 | 2.184* | 0.063 | 8.882 | 0.000 |
| | 35-39 | 2.391* | 0.063 | 10.924 | 0.000 |
| | 40-44 | 2.530* | 0.064 | 12.553 | 0.000 |
| | 2.639 | 0.064* | 0.066 | 1.070 | 0.000 |
| Place of residence | Urban(Ref) | | | | |
| | Rural | 0.236 | 0.018 | 1.266 | 0.000* |

| | | | | | |
|---|---|---|---|---|---|
| Religion | Ortodox | | | | |
| | Catolica | 0.040 | 0.080 | 1.041 | 0.600 |
| | Protestant | 0.138 | 0.020 | 1.148 | 0.000* |
| | Muslim | 0.215 | 0.017 | 1.240 | 0.000* |
| | Traditional | 0.091 | 0.073 | 1.095 | 0.213 |
| | Other | 0.150 | 0.119 | 1.162 | 0.209 |
| Sex of household | Male(Ref) | | | | |
| | Female | -0.039 | 0.021 | .677 | 0.003* |
| Age of household | | -0.002 | 0.001 | 0.998 | 0.000* |
| Economic status (wealth index) | Poor(Ref) | | | | |
| | Middle | -0.12 | 0.021 | .887 | 0.000* |
| | Rich | -0.22 | 0.016 | .80 | 0.000* |
| Current contraception use | Yes(Ref) | | | | |
| | No | 0.038 | 0.017 | 1.040 | 0.000* |
| Marital status | Unmarried(Ref) | | | | |
| | Married | 2.766 | 0.0998 | 15.89 | 0.000* |
| | other | 2.430 | 0.101 | 11.360 | 0.000* |
| Age at first birth | <=15(Ref) | | | | |
| | 16-19 | -0.182 | 0.017 | 0.834 | 0.000* |
| | >=20 | -0.524 | 0.018 | 0.592 | 0.000* |
| Constant | cons($\beta_0$) | -3.500 | 0.114 | 0.030 | 0.000* |
| Deviance based chi-square | 96 | | 0.000* | | |
| AIC | 23390.55 | | | | |
| BIC | 23546.57 | | | | |

Ref: reference Category,*Significance(P-value<0.05)

When we compare the fitted random coefficient and the random intercept fixed effect models, the random coefficient model was fitted to explain the regional differences of fertility perr mother’s ($\chi 2\ cal$= -2(LL-LLmodel)=-2(-11625-(-11673.27))=96. with P−value<0.05). All predictor variables were found to be significant in the random coefficient model.

### 4.5. Discussion of the Results

The main aim of this study was to identify the determinants of fertility statues using Ethiopian Mini demographic and health survey (EMDHS 2019) data using count regression models of factors which is associated with fertility among women in Ethiopia.

According to the descriptive result, out of all the women included in the study, 35. % did not have children during the survey period, and 65.5% of mothers had children for various reasons. Among the potential count models, the best fit count regression model was chosen.

The Multilevel Poisson Regression Model was shown to be the most suitable count model for Ethiopia's living children population. This section of the discussion tries to provide some explanation of the Multilevel Poisson regression model's conclusions about the impact of socioeconomic and demographic characteristics on the number of children in relation to prior research and theoretical background.Factors influencing the number of live children taken into account in this study include the current age of the highest level of education, region, place of residence, religion, sex and age as the head of the household, wealth index, marital status, and age at her first birth. Ten of the eleven variables that have been determined to be determinants of the number of living children in Ethiopia were found to be the subject of the empirical analysis of this study.

Based on the result of this study, Majority of the respondents (nearly 66.8%) in the sample were from rural places of residence while the rest 33.2% were from the urban parts of Ethiopia. another

The results of this study demonstrated that rural women have a 22% higher average number of living children per mother. It is supported by other findings (Götmark & Andersson, 2020) . A Botswana study that discovered a 1.22 percent decline in the number of living children among those who live in cities supports this conclusion (22%)(H. Kiser & Hossain, 2019b) . This might be as a result of rural women's limited access to family planning and educational possibilities, both of which have an impact on behavior. Moreover, Hossain et al. (2020) observed no statistically significant difference in the number of living children per mother provided to women in Bangladesh living in urban and rural locations. Families in metropolitan locations may be forced to limit the number of children they have since they have less resources, including housing (Kulu, 2013).

The respondent's age increased along with the number of live children. The percentage change in the rate of children ever born when the mother's age group was between 45-49 is 14.54 times larger than that of the reference age groups (15-19), increasing by 54% for each unit rise in the respondents' current age. This result is consistent with research done on women in Nepal[(Tsegaye Negash, 2023)]. This indicates that among married women of reproductive age in Nepal and Ethiopia, the number of living children approximately doubles with each additional year of age. Among respondents included in this study, nearly 40.9% of the women were Muslim and 37.97% of them were orthodox while 0.88% were catholic and 0.3% were others. An early first birth (60.92%) happens at mother's age below 20 years old. and The wealth index indicates that 49.47% of the study subjects were from rich households and 15.10% from middle economic status.

According to the results of this study, Somali regions show the highest level of fertility as compared to Tigray which is somehow similar with previous studies ((Mulugeta Eyasu, 2015)). Comparing Addis Ababa to other locations, the city has lower fertility, which may be attributed to women's easier access to family planning knowledge and technologiesThis could be women in rural areas married younger, use contraceptives less frequently, and believe that children are a gift from God or Allah. This shows the existence of high fertility in rural women which is similar to studies in Nigeria (Chimere–Dan, 1990). This might be due to the fact that rural women have less habit of contraceptive use, an early marriage and due to religious perspectives that children are a gift of God or Allah.

The wealth index, which measures a household's economic condition, is one of the determining variables that significantly influences fertility. Numerous studies have shown that families attempt to reduce the number of children when family income rises because they want to provide their children with a high-quality existence. This demonstrates the inverse link between the number of children and economic status..This finding is supported by a study done in Kenya, which discovered that, in comparison to families with poor wealth indices, having a middle-income or rich wealth index family lowers the number of children born (Götmark & Andersson, 2020).

Studies on demographics in societies where contraception is either frequently or never used; demonstrate a positive correlation between women's age and fertility; however, in cases where contraception is widely used, there may be no direct correlation between fertility and the average age of the household (Oyefara, 2014). Current age of mother is a significant variable at 5% level of significance and supports the finding of (SUNMOLA, 2021).

# 5. CONCLUSION AND RECOMMENDATIONS

## 5.1. Conclusion

Using data from the 2019 EDHS, the aim of this study was to determine socioeconomic and demographic parameters that are connected to the number of live children per mother in Ethiopia. There are 8,855 women between the ages of 15 and 19 in this study. According to the descriptive result, 3113 women (35.0%) had no children, whereas 65% of mothers had children.

The most suited model was chosen for this investigation. Log-likelihood, the likelihood ratio test (LRT), and the information criterion AIC and BIC for nested models were used to perform the compression.The result also revealed that Poisson model was found to be the most appropriate model to predict the number of living children per mother in Ethiopia for single level analysis model.The likelihood ratio test (LRT) was used to determine whether there was heterogeneity in the number of children according to areas before moving on to the multilevel method data analysis. Given that multilevel count regression models fit more closely than single level count regression models, by the LRT.

The multilevel Poisson regression model was determined to be the most suitable model to fit the number of living children per mother after comparing those models based on model comparison methods (criteria) among multilevel count regression models. Additionally, out of the three multilevel Poisson regression models, the random-intercept model delivered the best fits for the number of living children per mother.

Lastly, as compared to other regions, the expected numbers of living children vary and are higher in Somalia, the SNNP, and Oromiyaa.

## 5.2. Recommendations

Based on the finding of this study we forward the following possible recommendation,

It is important to take into account any interference that aims to delay the age of first birth using organized women and men involved in health extension, religious groups consisting of one to five arrangements, religious leaders, family planning, and counseling.

- It is important to focus on empowering women and strengthening programs that promote the use of contraceptives in rural areas in order to reduce unwanted reproduction, especially in regions like Somalia.
- The minister of health and other stakeholders should consider whether the existing national family planning program is required in order to increase the quality and quantity of contraceptive use and achieve higher use and effectiveness that will lead to a greater contribution to fertility decline, especially in areas where fertility is high.
- To further understand the issue and propose a solution, more researchers in the field should take into account other significant elements that were overlooked and concentrate on those regions with high fertility.

# REFERENCES

*Ainsworth, M., Beegle, K., Nyamete, A., Ainsworth, M., Beegle, K., & Nyamete, A. (1996). The Impact of Women's Schooling on Fertility and Contraceptive Use: A Study of Fourteen Sub-Saharan African Countries. The World Bank Economic Review, 10(1),*

*Akmam, W. (2002). Women's Education and Fertility Rates in Developing Countries, With Special Reference to Bangladesh.*

*Alo, O. A. (2011). Fertility Regimentation of the Rural Yoruba Women of South-west Nigeria: The Case of Ido and Isinbode. Journal of Social Sciences, 26(1), 57–65.*

*An Overview of the Determinants of High Fertilily in Ethiopia | Ethiopian Journal of Development Research. (n.d.). Retrieved January 27, 2024, from*

*Atella, V., Rosati, F., Atella, V., & Rosati, F. (2000). Uncertainty about children's survival and fertility: A test using indian microdata. Journal of Population Economics,*

*Ayele, D. G. (2015). Determinants of fertility in Ethiopia. African Health Sciences, 15(2),*

*Becker, G., Lewis, H. G., Becker, G., & Lewis, H. G. (1973). On the Interaction between the Quantity and Quality of Children. Journal of Political Economy, 81(2), S279-88.*

*Becker, G. S. (Gary S. (1976). The economic approach to human behavior. 314.*

*Becker, G. S., & Lewis, H. G. (1973). On the Interaction between the Quantity and Quality of Children.*

*Behrman, J. R., & Wolfe, B. L. (1984). A More General Approach to Fertility Determination in a Developing Country: The Importance of Biological Supply Considerations, Endogenous Tastes and Unperceived Jointness. Economica, 51(203), 319.*

*Bongaarts, J. (1978). A Framework for Analyzing the Proximate Determinants of Fertility. Population and Development Review, 4(1), 105.*

*Bongaarts, J. (1994). The Impact of Population Policies:*

*Bongaarts, J. (2010). The causes of educational differences in fertility in sub-Saharan Africa. Poverty, Gender, and Youth.*

*Bongaarts, J. (2011). Can family planning programs reduce high desired family size in Sub-Saharan Africa? International Perspectives on Sexual and Reproductive Health,*

*Bove, R., & Valeggia, C. (n.d.). Polygyny and women's health in sub-Saharan Africa.*

*Breslow, N. E., & Clayton, D. G. (1993). Approximate Inference in Generalized Linear Mixed Models. Journal of the American Statistical Association, 88(421), 9–25.*

*Chimere–Dan, O. (1990). Determinants of rural and urban fertility differentials in Nigeria. Journal of Biosocial Science, 22(3), 293–303.*

*Christoffersen, B., Mahjani, B., Clements, M., Kjellström, H., & Humphreys, K. (2023). Quasi-Monte Carlo Methods for Binary Event Models with Complex Family Data. Journal of Computational and Graphical Statistics, 32(4), 1393–1401.*

*Colin, C. A., & Pravin, T. (2013). Regression analysis of count data, Second edition. Regression Analysis of Count Data, Second Edition, 1–567.*

*Ding, Q. J., & Hesketh, T. (2006). Family size, fertility preferences, and sex ratio in China in the era of the one child family policy: Results from national family planning and reproductive health survey. British Medical Journal, 333(7564), 371–373.*

*Dommaraju, P., & Agadjanian, V. (2009). India's north-south divide and theories of fertility change. Journal of Population Research, 26(3), 249–272.*

*Easterlin, R. A., & Crimmins, E. M. (1985). The fertility revolution : a supply-demand analysis. 209.*

*Gauthier, A. H., Smeeding, T. M., & Furstenberg, F. F. (2004). Are parents investing less time in children? Trends in selected industrialized countries.*

*Gebremedhin, M., Ambaw, F., Admassu, E., & Berhane, H. (2015). Maternal associated factors of low birth weight: A hospital based cross-sectional mixed study in Tigray, Northern Ethiopia. BMC Pregnancy and Childbirth, 15(1), 1–8.*

*Goldstein, H. (2011). Multilevel Statistical Models (Google eBook). 382.*

*Götmark, F., & Andersson, M. (2020). Human fertility in relation to education, economy, religion, contraception, and family planning programs. BMC Public Health, 20(1), 1–17.*

*Haq, I., Hossain, M. I., Saleheen, A. A. S., Nayan, M. I. H., Afrin, T., & Talukder, A. (2022). Factors Associated with Women Fertility in Bangladesh: Application on Count Regression Models. Current Women s Health Reviews, 19(2).*

*Haque, A., Hossain, T., & Nasser, M. (2015). Predicting the number of children ever born using logistic regression model. Biometrics & Biostatistics International Journal, Volume 2*

*Harttgen, K., & Misselhorn, M. (2006). A Multilevel Approach to Explain Child Mortality and Undernutrition in South Asia and Sub-Saharan Africa. Ibero America Institute for Econ. Research (IAI) Discussion Papers.*

*Hasinur Rahaman Khan, M., & Shaw, J. E. H. (2021). Multilevel Logistic Regression Analysis Applied to Binary Contraceptive Prevalence Data. Journal of Data Science, 93–110.*

*Hoffman, J. R., Delaney, M. A., Valdes, C. T., Herrera, D., Washington, S. L., Aghajanova, L., Smith, J. F., & Herndon, C. N. (2020).*

*Hox, J. J., Moerbeek, M., & van de Schoot, R. (2017). Multilevel Analysis : Techniques and Applications, Third Edition. Multilevel Analysis.*

*Hussen, N. M. (2022). Application of two level count regression modeling on the determinants of fertility among married women in Ethiopia. BMC Women's Health, 22(1), 1–8.*

*Joshi, S., & Schultz, T. P. (2013). Family Planning and Women's and Children's Health: Long-Term Consequences of an Outreach Program in Matlab, Bangladesh.*

*Jula, N. (2014). Multilevel model analysis using R. Revista Română de Statistică, 62(2),*

*Kabeer, N. (2001). Ideas, Economics and "the Sociology of Supply": Explanations for Fertility Decline in Bangladesh. Journal of Development Studies, 38(1), 29–70.*

*Kiser, H., & Hossain, M. A. (2019a). Estimation of number of ever born children using zero truncated count model: evidence from Bangladesh Demographic and Health Survey. Health Information Science and Systems, 7(1).*

*Kiser, H., & Hossain, M. A. (2019b). Estimation of number of ever born children using zero truncated count model: evidence from Bangladesh Demographic and Health Survey. Health Information Science and Systems, 7(1).*

*Kiser, C. V., Grabill, W. H., & Campbell, A. A. (1968). Trends and variations in fertility in the United States. 338.*

*Kravdal, Ø. (2002). Education and fertility in Sub-Saharan Africa: Individual and community effects. Demography, 39(2), 233–250.*

*Lam, D. ;, & Elsayed, A. (n.d.). Labour markets in low-income countries: Challenges and opportunities.*

*Long, J. S., Freese, J., Long, J. S., & Freese, J. (2006). Regression Models for Categorical Dependent Variables using Stata, 2nd Edition. 527.*

*Matsumoto, Y., & Yamabe, S. (2013). Family size preference and factors affecting the fertility rate in Hyogo, Japan. Reproductive Health, 10(1), 1–8.*

*Mekonnen, W., & Worku, A. (2011a). Determinants of fertility in rural Ethiopia: the case of Butajira Demographic Surveillance System (DSS).*

*Mekonnen, W., & Worku, A. (2011b). Determinants of low family planning use and high unmet need in Butajira District, South Central Ethiopia. Reproductive Health, 8(1).*

*Miranda, A. (2010). A double-hurdle count model for completed fertility data from the developing world. DoQSS Working Papers.*

*Moghimbeigi, A., Eshraghian, M. R., Mohammad, K., & McArdle, B. (2009). A score test for zero-inflation in multilevel count data. Computational Statistics & Data Analysis, 53(4),* *1239–1248.*

*Mulugeta Eyasu, A. (2015). Multilevel Modeling of Determinants of Fertility Status of Married Women in Ethiopia. American Journal of Theoretical and Applied Statistics, 4(1), 19.*

*Nations, U., of Economic, D., Affairs, S., & Division, P. (n.d.). World Population Prospects 2019 Highlights.*

*Osili, U. O., & Long, B. T. (2008). Does female schooling reduce fertility? Evidence from Nigeria. Journal of Development Economics, 87(1), 57–75.*

*Oyefara, J. L. (2014). Mothers' Characteristics and Immunization Status of Under-Five Children in Ojo Local Government Area, Lagos State, Nigeria.*

*Peden, A. R., Rayens, M. K., Hall, L. A., & Beebe, L. H. (2001). Preventing depression in high-risk college women: a report of an 18-month follow-up. Journal of American College Health : J of ACH, 49(6), 299–306.*

*Rahman, A., Hossain, Z., Rahman, M. L., & Kabir, E. (2022). Determinants of children ever born among ever-married women in Bangladesh: evidence from the Demographic and Health Survey 2017–2018.*

*Saadati, M. (2015). Factors Affecting Children Ever Born for 15-49 Year -Old Women in Semnan Using Poisson Regression. Journal of Health System Research, 11(3), 627–637.*

*Saporta, G. (2006). Probabilités, analyse des données et statistique. 622.*

*Sennott, C., & Yeatman, S. (2012). Stability and Change in Fertility Preferences Among Young Women in Malawi. International Perspectives on Sexual and Reproductive Health, 38(1),*

*Sturman, M. C. (1999). Multiple Approaches to Analyzing Count Data in Studies of Individual Differences: The Propensity for Type I Errors, Illustrated with the Case of Absenteeism Prediction.*

*SUNMOLA, A. (2021). Contextual Determinants of Children Ever Born Among Women of Reproductive Age in Selected Southwest State in Nigeria. European Journal of Sociology.*

*Tsegaye Negash, B. (2023). Fertility intention among married women in Ethiopia: a multilevel analysis of Ethiopian demographic health survey 2016. Contraception and Reproductive Medicine 2023 8:1, 8(1), 1–10.*

*Wang, W., & Famoye, F. (1997). Modeling household fertility decisions with generalized Poisson regression. Journal of Population Economics, 10(3), 273–283.*

*Yaya, S., Uthman, O. A., Amouzou, A., Ekholuenetale, M., & Bishwajit, G. (2018). Inequalities in maternal health care utilization in Benin: A population based cross-*

*sectional study.*

*Yitayal Melese, Z., & Bewuket Zeleke, L. (2020). Factors Affecting Children Ever Born Among Reproductive Aged Women in Ethiopia; Data from Edhs 2016. World Journal of Public Health, 5(3), 66.*

# Appendix

## Appendix A

tab Marstats NLC, col ch

tabulate Marstats NLC, summarize(NLC)

**Table A1. the percentage of regional differential of women by selected socio demographic variables in fertility.**

| Variable | | Tigray | Afar | Amhara | Oromia | Somali | Benishang | SNNPR | Gambela | Harari | Adiss Ababa | Dira Dawa | total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Current age | 15-19 | 22.78 | 19.7 | 23.5 | 26.24 | 27.0 | 24.9 | 23.3 | 24.48 | 22.8 | 21.03 | 23.5 | 23.64 |
| | 20-24 | 18.01 | 20.4 | 14.9 | 17.40 | 15.9 | 16.7 | 13.6 | 16.60 | 19.4 | 21.39 | 22.7 | 17.76 |
| | 25-29 | 16.78 | 22.8 | 17.1 | 17.02 | 19.8 | 20.6 | 21.7 | 19.64 | 20.5 | 24.45 | 17.7 | 19.72 |
| | 30-34 | 15.42 | 14.5 | 13.6 | 12.45 | 14.4 | 11.5 | 12.9 | 14.25 | 13.6 | 13.08 | 9.73 | 13.12 |
| | 35-39 | 11.05 | 9.98 | 13.7 | 11.79 | 10.8 | 10.8 | 13.1 | 13.69 | 11.9 | 10.02 | 10.3 | 11.67 |
| | 40-44 | 9.28 | 8.74 | 8.97 | 9.41 | 6.88 | 6.83 | 8.63 | 7.05 | 7.47 | 5.87 | 8.37 | 8.04 |
| | 45-49 | 6.68 | 4.06 | 8.23 | 5.70 | 5.16 | 8.57 | 6.75 | 4.29 | 4.33 | 4.16 | 7.64 | 6.06 |
| ATFB | <=15 | 11.73 | 24.9 | 25.4 | 23.67 | 13.8 | 26.2 | 29.2 | 32.78 | 16.4 | 4.77 | 11.9 | 20.39 |
| | 16-19 | 47.89 | 40.3 | 42.9 | 47.72 | 43.1 | 43.4 | 39.5 | 45.50 | 36.4 | 22.37 | 36.3 | 40.53 |
| | >=20 | 40.38 | 34.8 | 31.7 | 28.61 | 43.1 | 30.4 | 31.4 | 21.72 | 47.2 | 72.86 | 51.7 | 39.08 |
| residen | Urba | 23.2 | 19.66 | 14.6 | 17.49 | 23.9 | 14.7 | 8.63 | 21.99 | 62.7 | 100.0 | 65.0 | 33.21 |
| | Rural | 76.8 | 80.34 | 85.4 | 82.51 | 76.1 | 85.3 | 91.4 | 78.01 | 37.4 | 0.00 | 34.9 | 66.79 |
| Religion | Orth. | 97.0 | 1.25 | 88.1 | 17.11 | 2.34 | 37.5 | 18.5 | 24.48 | 27.4 | 70.54 | 24.0 | 37.97 |
| | Catho | 0.00 | 0.31 | 0.11 | 0.00 | 0.00 | 0.00 | 2.68 | 4.43 | 0.79 | 0.61 | 0.62 | 0.88 |
| | Protest | 0.14 | 0.94 | 0.11 | 35.55 | 0.00 | 11.1 | 64.7 | 57.68 | 5.24 | 10.51 | 6.28 | 19.26 |
| | Musli | 2.86 | 97.50 | 11.7 | 44.96 | 97.7 | 49.4 | 11.7 | 10.79 | 66.5 | 18.09 | 68.9 | 40.91 |
| | Tradit. | 0.00 | 0.00 | 0.00 | 2.38 | 0.00 | 2.01 | 1.39 | 0.83 | 0.00 | 0.00 | 0.00 | 0.68 |
| | Other | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.11 | 0.15 | 0.01 | 0.02 | 0.01 | 0.30 |
| SHH | Male | 70.8 | 55.69 | 81.2 | 88.12 | 51.6 | 82.9 | 87.0 | 62.38 | 65.0 | 59.78 | 67.1 | 71.81 |
| | Fema | 29.2 | 44.31 | 18.8 | 11.88 | 48.4 | 17.1 | 13.0 | 37.62 | 34.9 | 40.22 | 32.8 | 28.19 |
| Econo.statsu | Poor | 2.40 | 5.64 | 3.22 | 4.04 | 5.83 | 3.86 | 3.92 | 3.69 | 0.72 | 0.08 | 2.04 | 35.43 |
| | middl | 14.5 | 6.86 | 27.2 | 19.87 | 9.06 | 19.7 | 19.4 | 16.87 | 11.7 | 6.60 | 7.39 | 15.10 |
| | riche | 56.5 | 14.98 | 42.6 | 46.01 | 10.0 | 34.4 | 46.1 | 37.76 | 79.9 | 92.54 | 70.3 | 49.47 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CU | No | 74.5 | 90.17 | 66.4 | 71.48 | 97.7 | 71.5 | 68.5 | 75.52 | 78.8 | 73.59 | 81.8 | 76.17 |
| | Yes | 25.5 | 9.83 | 33.7 | 28.52 | 2.34 | 28.5 | 31.5 | 24.48 | 21.2 | 26.41 | 18.2 | 23.83 |
| Marital | Unma. | 26.5 | 12.95 | 22.1 | 25.86 | 23.9 | 22.6 | 25.3 | 19.50 | 29.1 | 43.89 | 29.8 | 25.89 |
| | Marr. | 59.6 | 74.57 | 66.0 | 67.59 | 68.9 | 70.0 | 69.3 | 59.34 | 59.2 | 44.87 | 55.5 | 63.17 |
| | Other | 13.9 | 12.48 | 11.8 | 6.56 | 7.19 | 7.36 | 5.46 | 21.16 | 11.7 | 11.25 | 14.7 | 10.94 |
| | Total | 100. | 100. | 100. | 100. | 100. | 100. | 100. | 100. | 100. | 100. | 100. | 100.00 |

Table 4.11:Summery statistics of predictor variables related to number of children in Ethiopia

| Respondants current age | Number living children | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Mean | std |
| 15-19 | 1,869 | 188 | 38 | 4 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | .133 | .411 |
| 20-24 | 733 | 445 | 267 | 90 | 34 | 9 | 0 | 0 | 0 | 0 | 0 | .906 | 1.07 |
| 25-29 | 312 | 318 | 418 | 305 | 207 | 110 | 58 | 21 | 1 | 1 | 1 | 2.27 | 1.72 |
| 30-34 | 88 | 107 | 177 | 194 | 206 | 181 | 115 | 65 | 22 | 10 | 1 | 3.60 | 2.06 |
| 35-39 | 61 | 71 | 127 | 123 | 184 | 159 | 142 | 82 | 54 | 21 | 13 | 4.25 | 2.33 |
| 40-44 | 30 | 48 | 42 | 71 | 103 | 105 | 117 | 96 | 64 | 26 | 12 | 4.95 | 2.43 |
| 45-49 | 20 | 27 | 46 | 54 | 69 | 80 | 83 | 67 | 48 | 10 | 34 | 5.12 | 2.60 |
| Region | | | | | | | | | | | | | |
| Tigray | 235 | 120 | 91 | 71 | 70 | 64 | 40 | 20 | 17 | 4 | 1 | 2.29 | 2.32 |
| Afar | 150 | 94 | 101 | 77 | 69 | 48 | 43 | 34 | 11 | 9 | 3 | 2.75 | 2.45 |
| Amhara | 310 | 135 | 119 | 94 | 107 | 76 | 49 | 35 | 16 | 4 | 1 | 2.32 | 2.33 |
| Oromia | 351 | 117 | 123 | 75 | 103 | 85 | 72 | 55 | 40 | 15 | 8 | 2.73 | 2.79 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Somali | 218 | 41 | 55 | 59 | 54 | 58 | 58 | 49 | 24 | 12 | 9 | 3.05 | 2.94 |
| Benishang | 232 | 102 | 82 | 74 | 88 | 63 | 51 | 30 | 17 | 3 | 4 | 2.52 | 2.45 |
| SNNPR | 321 | 87 | 112 | 103 | 102 | 98 | 87 | 49 | 28 | 11 | 6 | 2.79 | 2.64 |
| Gambela | 207 | 121 | 92 | 86 | 78 | 59 | 56 | 15 | 8 | 1 | 0 | 2.33 | 2.17 |
| Harari | 292 | 111 | 113 | 79 | 60 | 40 | 31 | 19 | 11 | 3 | 2 | 1.95 | 2.24 |
| Addis Ad | 448 | 142 | 120 | 65 | 23 | 13 | 4 | 2 | 1 | 0 | 0 | .95 | 1.3 |
| Dira Dawa | 349 | 134 | 107 | 58 | 50 | 40 | | 24 | 23 | 16 | 6 | | 4 |

Place of Residence

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Urban | 1,323 | 512 | 438 | 261 | 157 | 99 | 59 | 52 | 32 | 11 | 7 | 1.51 | 1.96 |
| Rural | 1,790 | 692 | 677 | 580 | 647 | 545 | 456 | 279 | 157 | 57 | 54 | 2.72 | 2.58 |
| Religion | | | | | | | | | | | | | |
| Orthodox | 1,331 | 540 | 431 | 315 | 271 | 197 | 148 | 81 | 43 | 11 | 6 | 1.89 | 2.17 |
| Catholic | 26 | 12 | 9 | 6 | 10 | 5 | 8 | 2 | 0 | 0 | 0 | 2.24 | 2.22 |
| Protestant | 560 | 210 | 229 | 159 | 163 | 142 | 115 | 64 | 44 | 15 | 10 | 2.47 | 2.50 |
| Muslim | 1,173 | 438 | 435 | 350 | 346 | 289 | 238 | 183 | 99 | 41 | 43 | 2.62 | 2.64 |
| Traditiona | 16 | 2 | 7 | 7 | 10 | 7 | 5 | 1 | 2 | 1 | 2 | 3.27 | 2.81 |
| Other | 7 | 2 | 4 | 4 | 4 | 4 | 1 | 0 | 1 | 0 | 0 | 2.67 | 2.20 |
| Sex of house hold | | | | | | | | | | | | | |
| Male | 2,082 | 801 | 828 | 630 | 619 | 499 | 399 | 264 | 151 | 57 | 50 | 2.48 | 2.51 |
| Female | 1,031 | 403 | 287 | 211 | 185 | 145 | 116 | 67 | 38 | 11 | 11 | 1.90 | 2.28 |
| Wealth index | | | | | | | | | | | | | |
| poor | 864 | 322 | 363 | 314 | 349 | 324 | 276 | 165 | 104 | 35 | 32 | 2.95 | 2.64 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| midle | 436 | 182 | 163 | 138 | 134 | 110 | 85 | 60 | 19 | 10 | 5 | 2.41 | 2.40 |
| riche | 1,813 | 700 | 589 | 389 | 321 | 210 | 154 | 106 | 66 | 23 | 24 | 1.83 | 2.23 |
| Contraceptive use | | | | | | | | | | | | | |
| No | 2,875 | 733 | 674 | 553 | 549 | 471 | 388 | 268 | 155 | 52 | 50 | 2.18 | 2.54 |
| Yes | 238 | 471 | 441 | 288 | 255 | 173 | 127 | 63 | 34 | 16 | 11 | 2.76 | 2.12 |
| Marital status | | | | | | | | | | | | | |
| Never in union | 2,242 | 40 | 7 | 2 | 2 | 3 | 3 | 1 | 0 | 0 | 0 | 0.05 | .39 |
| Married | 648 | 922 | 952 | 727 | 715 | 578 | 469 | 304 | 173 | 65 | 36 | 3.26 | 2.40 |
| Other | 223 | 242 | 156 | 112 | 87 | 63 | 43 | 26 | 16 | 3 | 1 | 2.22 | 2.09 |
| Age at first birth | | | | | | | | | | | | | |
| <=15 | 223 | 125 | 203 | 233 | 269 | 249 | 213 | 144 | 83 | 38 | 32 | 3.97 | 2.56 |
| 16-19 | 1,399 | 459 | 434 | 332 | 313 | 233 | 182 | 135 | 75 | 20 | 19 | 2.15 | 2.41 |
| =>20 | 1,491 | 620 | 478 | 276 | 222 | 162 | 120 | 52 | 31 | 10 | 10 | 1.62 | 2.03 |

. poisson NLC i.AGE i.Region i.POR i.REL i.SHH AHH i.wealthind i.contuse i.Marstats i.AAFA_1,nopvalues

**Table 4.12: Result of the Poisson and Negative Binomial mode**

| NLC | Coef. | Std. Err. | [95% Conf. | Interval] |
|---|---|---|---|---|
| AGE | | | | |
| 20-24 | 1.105777 | .0663 | .9757025 | 1.235852 |
| 25-29 | 1.80558 | .0632 | 1.681606 | 1.929554 |
| 30-34 | 2.18436 | .0633 | 2.060294 | 2.308426 |
| 35-39 | 2.391435 | .0634 | 2.26707 | 2.5158 |
| 40-44 | 2.529521 | .0643 | 2.403338 | 2.655705 |
| 45-49 | 2.639102 | .0655 | 2.51054 | 2.767665 |

| | | | | |
|---|---|---|---|---|
| Region | | | | |
| Afar | -.1328811 | .0410 | -.2133599 | -.0524024 |
| Amhara | -.18198 | .0328 | -.2463358 | -.1176242 |
| Oromia | -.057156 | .0353 | -.1263999 | .0120878 |
| Somali | .0702921 | .0405 | -.0092691 | .1498533 |
| Benishan | -.1493535 | .036 | -.2207988 | -.0779082 |
| SNNPR | -.0775011 | .0366 | -.1493545 | -.0056477 |
| Gambela | -.184652 | .0393 | -.2618587 | -.1074467 |
| Harari | -.116915 | .04090 | -.1970837 | -.0367462 |
| Addis Adaba | -.325 | .048 | -.4197643 | -.2312222 |
| Dire Dawa | -.1517 | .041 | -.2319136 | -.0715176 |
| POR | | | | |
| Rural | .1917445 | .0202 | .1520088 | .2314801 |
| REL | | | | |
| Catholic | .0614413 | .079 | -.0937721 | .2166546 |
| Protestant | .1277711 | .0259676 | .0768757 | .1786666 |
| Muslim | .1903377 | .0226 | .1458534 | .2348219 |
| Traditional | .0875 | .0745 | -.0585603 | .2336664 |
| Other | .1557422 | .1203 | -.0800613 | .3915458 |
| SHH | | | | |
| Female | -.0482565 | .0207 | -.0889971 | -.0075158 |
| AHH | -.0018823 | .000692 | -.0032402 | -.0005243 |
| wealthind | | | | |
| midle | -.1007872 | .02146 | -.1428567 | -.0587177 |
| riche | -.1927023 | .0175 | -.2270242 | -.1583804 |
| contuse | | | | |
| Yes | .0477425 | .0167965 | .0148219 | .0806631 |
| Marstats | | | | |
| Married | 2.75206 | .09993 | 2.55619 | 2.947935 |
| Other | 2.438886 | .10177 | 2.23942 | 2.638351 |
| AAFA_1 | | | | |
| 16-19 | -.1936381 | .01672 | -.2264167 | -.1608595 |
| =>20 | -.5321944 | .01843 | -.5683351 | -.4960536 |
| _cons | -3.340797 | .11649 | -3.569129 | -3.112466 |

*nbreg NLC i.AGE i.Region i.POR i.REL i.SHH AHH i.wealthind i.Marstats i.contuse i.AAFA_1,dispersion(mean) nopvalues*

| NLC | Coef. | Std. Err. | [95% Conf. | Interval] |
|---|---|---|---|---|
| AGE | | | | |
| 20-24 | 1.105777 | .0663658 | .9757025 | 1.235852 |
| 25-29 | 1.80558 | .0632533 | 1.681606 | 1.929554 |

| | | | | |
|---|---|---|---|---|
| 30-34 | 2.18436 | .0633003 | 2.060294 | 2.308426 |
| 35-39 | 2.391435 | .0634527 | 2.26707 | 2.5158 |
| 40-44 | 2.529521 | .0643807 | 2.403338 | 2.655705 |
| 45-49 | 2.639102 | .0655943 | 2.51054 | 2.767665 |
| Region | | | | |
| Afar | -.1328811 | .0410613 | -.2133599 | -.0524024 |
| Amhara | -.18198 | .0328352 | -.2463358 | -.1176241 |
| Oromia | -.057156 | .0353292 | -.1263999 | .0120878 |
| Somali | .0702921 | .0405932 | -.0092691 | .1498533 |
| Benishangul | -.1493535 | .0364524 | -.2207988 | -.0779082 |
| SNNPR | -.0775011 | .0366606 | -.1493545 | -.0056477 |
| Gambela | -.1846527 | .0393915 | -.2618587 | -.1074467 |
| Harari | -.116915 | .0409032 | -.1970837 | -.0367462 |
| Addis Adaba | -.3254932 | .0480983 | -.4197643 | -.2312222 |
| Dire Dawa | -.1517156 | .0409181 | -.2319136 | -.0715176 |
| POR | | | | |
| Rural | .1917445 | .0202737 | .1520088 | .2314801 |
| REL | | | | |
| Catholic | .0614413 | .079192 | -.0937721 | .2166547 |
| Protestant | .1277711 | .0259676 | .0768757 | .1786666 |
| Muslim | .1903377 | .0226964 | .1458534 | .2348219 |
| Traditional | .0875531 | .074549 | -.0585603 | .2336664 |
| Other | .1557422 | .1203101 | -.0800613 | .3915458 |
| SHH | | | | |
| Female | -.0482565 | .0207864 | -.0889971 | -.0075158 |
| AHH | -.0018823 | .0006929 | -.0032402 | -.0005243 |
| wealthind | | | | |
| midle | -.1007872 | .0214644 | -.1428567 | -.0587177 |
| riche | -.1927023 | .0175115 | -.2270242 | -.1583804 |
| Marstats | | | | |
| Married | 2.752063 | .0999366 | 2.55619 | 2.947935 |
| Other | 2.438886 | .10177 | 2.23942 | 2.638351 |
| contuse | | | | |
| No | .0477425 | .0167965 | .0148219 | .0806631 |
| AAFA_1 | | | | |
| 16-19 | -.1936381 | .0167241 | -.2264167 | -.1608595 |
| =>20 | -.5321944 | .0184395 | -.5683351 | -.4960536 |
| _cons | -3.340798 | .1164976 | -3.569129 | -3.112466 |
| /lnalpha | -17.07325 | 64.98851 | -144.4484 | 110.3019 |
| alpha | 3.85e-08 | 2.50e-06 | 1.85e-63 | 8.01e+47 |
| LR test of alpha=0: chibar2(01) = 0.0e+00 Prob >= chibar2 = 0.500 | | | | |

**Multilevel Poisson regression model**

Output 1. Result of empty single level Poisson regression model

. poisson NLC

| NLC | Coef. | Std. Err. | z | P>z | [95% Conf. Interval] |
|---|---|---|---|---|---|
| _cons | .8395179 | .0069722 | 120.41 | 0.000 | .8258525 .8531832 |

. estat ic

Akaike's information criterion and Bayesian information criterion

| Model | Obs | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| . | 8,885 | -21316.09 | -21316.09 | 1 | 42634.19 | 42641.28 |

Note: N=Obs used in calculating BIC; see [R] BIC note.

**Outpute 2: Result of empty Multilevel Poisson regression model**

**. mepoisson NLC Region, Region:, covariance(identity)**

Fitting fixed-effects model:

Mixed-effects Poisson regression Number of obs = 8,885

Group variable: Region Number of groups = 11

Obs per group:

min = 640

avg = 807.7

max = 1,052

Integration method: mvaghermite Integration pts. = 7

Wald chi2(1) = 28.21

Log likelihood = -20686.299 Prob > chi2 = 0.0000

| NLC | Coef. | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| Region | -.1503387 | .0283065 | -5.31 | 0.000 | -.2058183 | -.0948591 |
| _cons | 1.470613 | .2783172 | 5.28 | 0.000 | .9251213 | 2.016105 |
| Region | | | | | | |
| var(_cons) | .2199404 | .1003018 | | | .0899752 | .537635 |

LR test vs. Poisson model: chibar2(01) = 832.34        Prob >= chibar2 = 0.0000

Akaike's information criterion and Bayesian information criterion

| Model | Obs | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| . | 8,885 | . | -20686.3 | 3 | 41378.6 | 41399.87 |

**Outpute 3.Result of random intercept multilevel Poisson Model**

Mixed-effects Poisson regression        Number of obs = 8,885

Group variable: Region        Number of groups = 11

Obs per group:

min = 640

avg = 807.7

max = 1,052

Integration method: mvaghermite        Integration pts. = 7

Wald chi2(21) = 7432.15

Log likelihood = -11625.313        Prob > chi2 = 0.0000

**Outpute 3.Result of random intercept multilevel Poisson Model**

**Table 4.13: Result of random intercept multilevel Poisson Model**

| NLC | Coef. | Std. Err. | Z | P>z | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| | | | AGE | | | |
| 20-24 | 1.10518 4 | .06636321 | 6.65 | 0.000 | .9751141 | 1.235253 |
| 25-29 | 1.80469 8 | .0632495 | 28.53 | 0.000 | 1.680731 | 1.928665 |
| 30-34 | 2.18389 8 | .0632953 | 34.50 | 0.000 | 2.059841 | 2.307954 |
| 35-39 | 2.39075 9 | .0634477 | 37.68 | 0.000 | 2.266403 | 2.515114 |
| 40-44 | 2.52916 2 | .064376 | 39.29 | 0.000 | 2.402987 | 2.655337 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 45-49 | 2.638622 | .0655855 | 40.23 | 0.000 | 2.510076 | 2.767167 |
| POR | | | | | | |
| Rural | .1978555 | .0201656 | 9.81 | 0.000 | .1583316 | .2373793 |
| REL | | | | | | |
| Catholic | .0597102 | .0789881 | 0.76 | 0.450 | .0951036 | .214524 |
| Protestant | .1283038 | .0254937 | 5.03 | 0.000 | .078337 | .1782706 |
| Muslim | .192905 | .0221493 | 8.71 | 0.000 | .1494932 | .2363168 |
| Traditional | .0874243 | .0744132 | 1.17 | 0.240 | .0584229 | .2332716 |
| Other | .1534735 | .1201707 | 1.28 | 0.202 | .0820568 | .3890038 |
| SHH | | | | | | |
| Female | -.0471708 | .0207397 | -2.27 | 0.023 | .0878199 | -.0065217 |
| AHH | -.0018811 | .0006926 | -2.72 | 0.007 | .0032386 | -.0005236 |
| wealthind | | | | | | |
| midle | -.1027768 | .0214235 | -4.80 | 0.000 | .1447661 | -.0607874 |
| riche | -.1960174 | .017468 | 11.22 | 0.000 | .2302542 | -.1617807 |
| contuse | | | | | | |
| No | .0468401 | .0167804 | 2.79 | 0.005 | .0139512 | .0797291 |
| Marstats | | | | | | |
| Married | 2.754458 | .0999286 | 27.56 | 0.000 | 2.558601 | 2.950314 |
| Other | 2.439551 | .1017567 | 23.97 | 0.000 | 2.240111 | 2.63899 |
| AAFA_1 | | | | | | |
| 16-19 | -.1930156 | .0167151 | 11.55 | 0.000 | .2257765 | -.1602546 |
| =>20 | -.5322894 | .0184173 | 28.90 | 0.000 | .5683868 | -.4961921 |
| _cons | -3.464258 | .1172909 | 29.54 | 0.000 | 3.694144 | -3.234372 |
| Region | | | | | | |
| var(_cons) | .0085351 | .0040399 | | | .0033753 | .0215829 |
| LR test vs. Poisson model: chibar2(01) = 95.92 Prob >= chibar2 = 0.0000 | | | | | | |

**. estat ic**

**Akaike's information criterion and Bayesian informationcriterion**

| Model | Obs | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| | | | | | | |
| **.** | **8,885** | **.** | **-11625.31** | **23** | **23296.63** | **23459.75** |

# Outpute 4.Result of random intercept and coefficient multilevel Poisson Model

mepoisson NLC i. REL i.wealthind i.contuse i.AAFA_1 i.SHH AHH, Region: POR, covariance(unstructured) cformat(%9.3f)

> pformat(%5.3f) sformat(%8.3f)

Fitting fixed-effects model:

Iteration 0: log likelihood = -22777.765

Iteration 21: log likelihood = -19052.036

Iteration 22: log likelihood = -19051.972

Iteration 23: log likelihood = -19051.972

Mixed-effects Poisson regression Number of obs = 8,885

Group variable: Region Number of groups = 11

Obs per group:

min = 640

avg = 807.7

max = 1,052

Integration method: mvaghermite Integration pts. = 7

Wald chi2(12) = 2856.64

Log likelihood = -19051.972 Prob > chi2 = 0.0000

**Table4.14: Result of random intercept and coefficient multilevel Poisson Model**

| NLC | Coef. | Std. Err. | z | P>z | [95% Conf. Interval] | |
|---|---|---|---|---|---|---|
| REL | | | | | | |
| Catholic | 0.030 | 0.079 | 0.382 | 0.702 | -0.125 | 0.185 |
| Protestant | 0.099 | 0.026 | 3.780 | 0.000 | 0.048 | 0.151 |
| Muslim | 0.222 | 0.023 | 9.482 | 0.000 | 0.176 | 0.268 |
| Traditional | 0.315 | 0.075 | 4.228 | 0.000 | 0.169 | 0.462 |
| Other | 0.132 | 0.120 | 1.100 | 0.271 | -0.103 | 0.368 |
| wealthind | | | | | | |
| midle | -0.165 | 0.021 | -7.677 | 0.000 | -0.207 | -0.123 |
| riche | -0.289 | 0.018 | -16.196 | 0.000 | -0.324 | -0.254 |
| contuse | | | | | | |
| Yes | 0.333 | 0.017 | 20.162 | 0.000 | 0.301 | 0.366 |

| |
|---|
| AAFA_1 |
| 16-19 -0.590 0.017 -35.626 0.000 -0.623 -0.558 |
| =>20 -0.754 0.019 -40.561 0.000 -0.791 -0.718 |
| SHH |
| Female -0.129 0.018 -7.240 0.000 -0.164 -0.094 |
| AHH 0.003 0.000 6.949 0.000 0.002 0.004 |
| _cons 0.657 0.049 13.325 0.000 0.561 0.754 |
| Region |
| var(POR) 0.094 0.044 0.037 0.235 |
| var(_cons) 0.102 0.052 0.037 0.278 |
| Region |
| cov(_cons,POR) -0.028 0.037 -0.762 0.446 -0.101 0.044 |

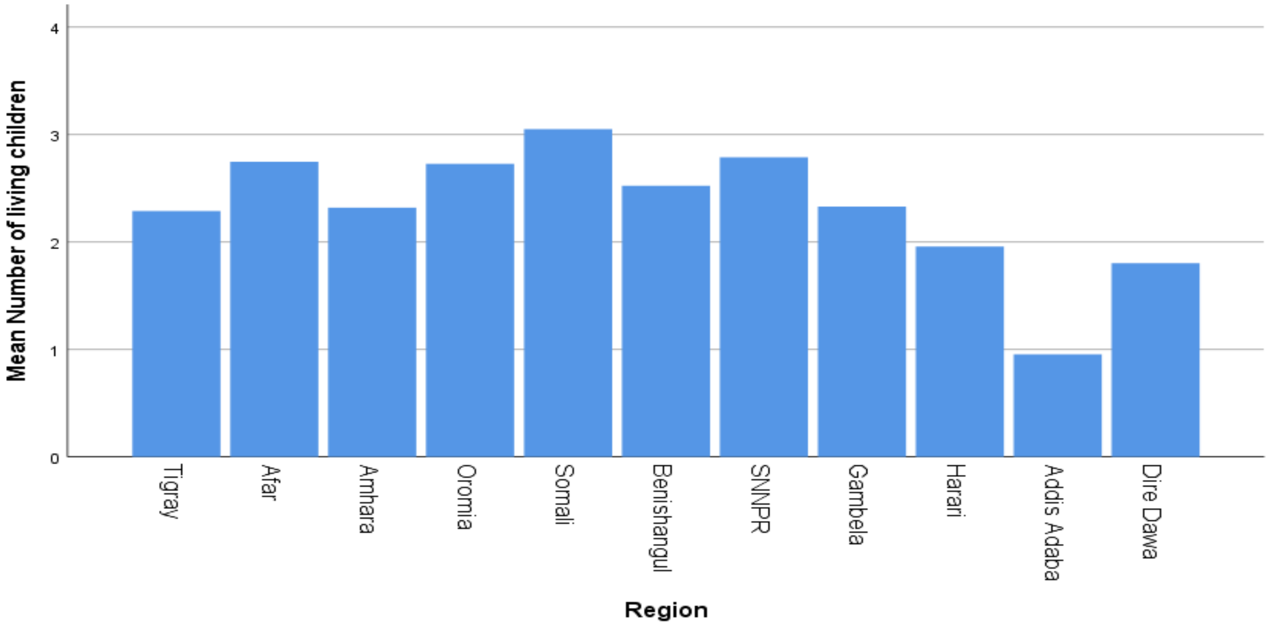
LR test vs. Poisson model: chi2(3) = 514.52 Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

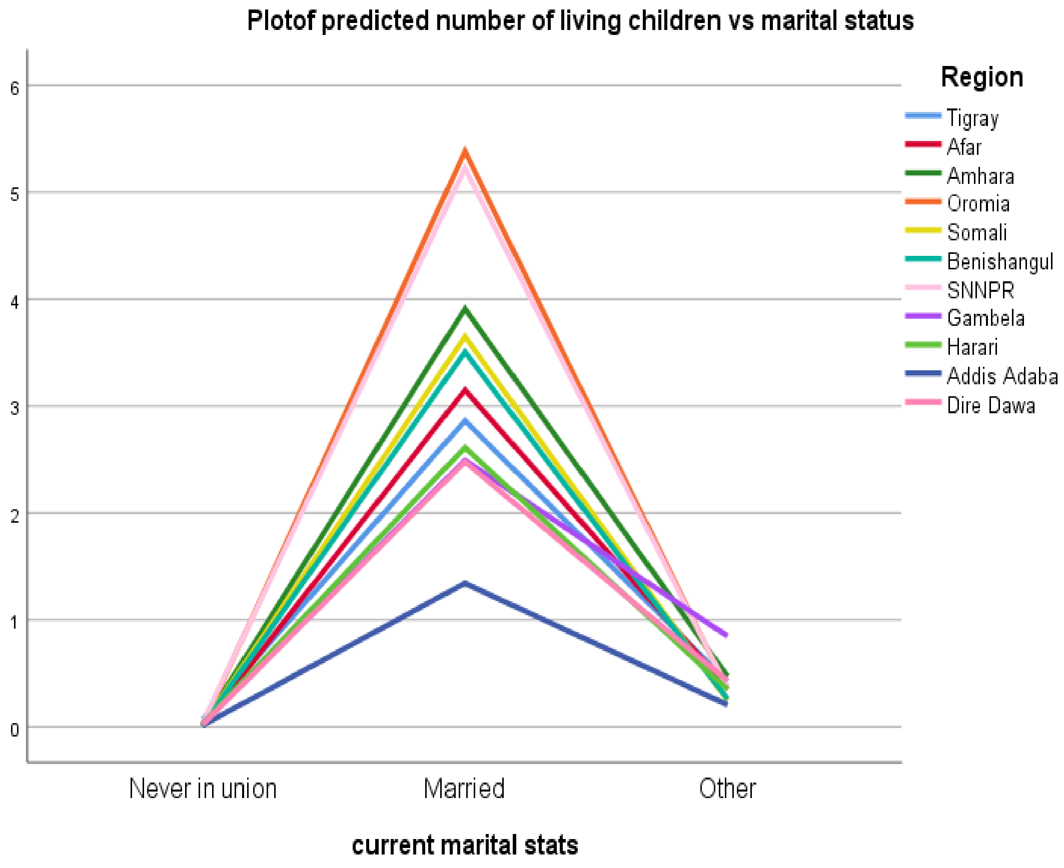
. estat ic

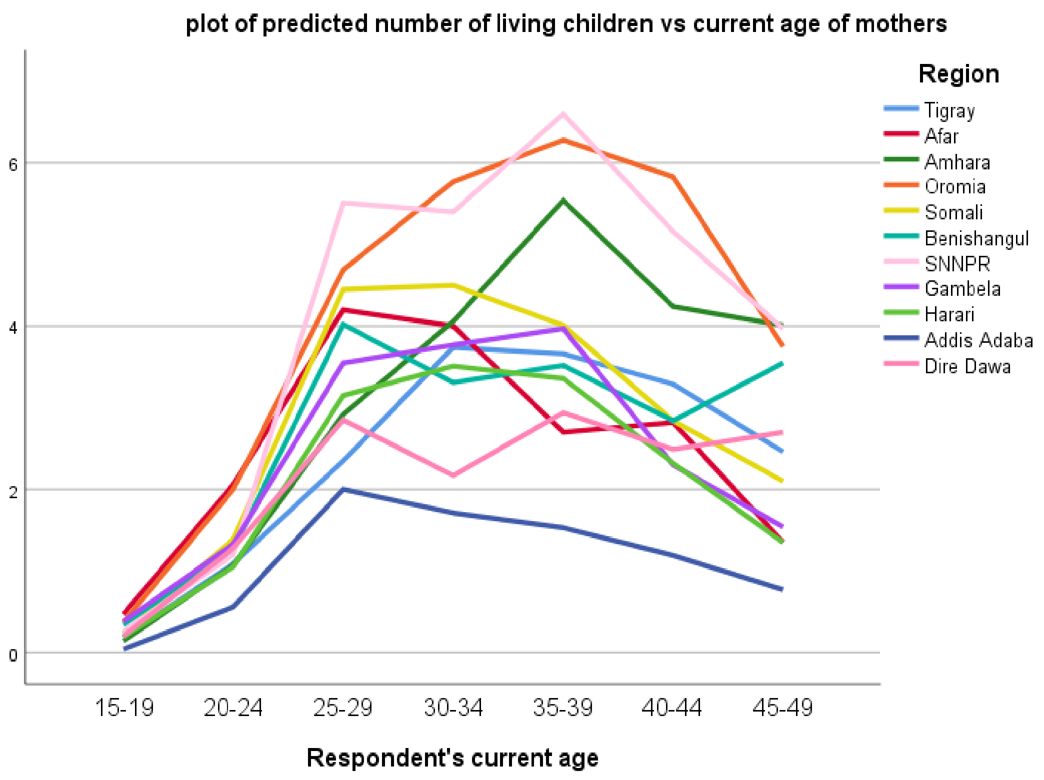
| |
|---|
| Akaike's information criterion and Bayesian information criterion |
| Model Obs ll(null) ll(model) df AIC BIC |
| . 8,885 . -19051.97 16 38135.94 38249.42 |

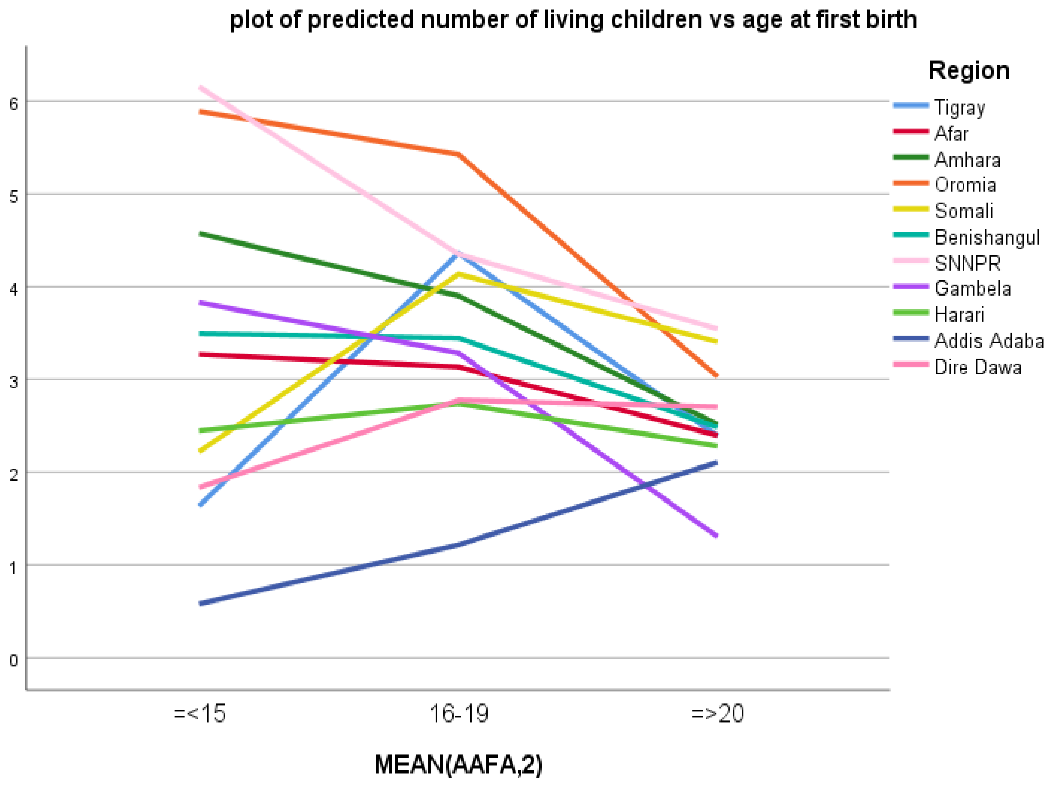
**FigureA4: Number of living children per women by Region**




Appendix B: **Multilevel poisson Regression results**


Plotof predicted number of living children vs marital status
Region
Tigray
Afar
Amhara
Oromia
Somali
Benishangul
SNNPR
Gambela
Harari
Addis Adaba
Dire Dawa
0
1
2
3
4
5
6
Never in union
Married
Other
current marital stats


plot of predicted number of living children vs current age of mothers
Region
Tigray
Afar
Amhara
Oromia
Somali
Benishangul
SNNPR
Gambela
Harari
Addis Adaba
Dire Dawa
0
2
4
6
15-19
20-24
25-29
30-34
35-39
40-44
45-49
Respondent's current age




Operationalization and Description of Socio-Demographic Variables