Modeling Determinants of Desired Number of Antenatal Care Visits among Pregnant Women in Ethiopia: Application of Multilevel Count Regression Models.

By

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MSc Thesis

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As thesis advisors, we hereby certify that we have read the thesis prepared by SALI SULEMAN under our guidance, which is entitled "**Modeling Determinants of Desired Number of Antenatal Care Visits among Pregnant Women in Ethiopia: Application of Multilevel Count Regression Models"** in its final format and consistent and acceptable. Hence, we recommend that the thesis be accepted as it fulfills the requirements for the degree of Master of Science in Biostatistics and is ready for submission to the university library.

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As the members of the board of examiners of MSc thesis open defense examination, we certify that we have read and evaluated the thesis and examined the candidate. Hence, we recommend that the thesis be accepted as it fulfills the requirements for the degree of Master of Science in Biostatistics.

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Dedication

This thesis is dedicated to my families especially to my father Suleman Hassen, my stepmother Amina Adelo, my brother Tahir Suleman and my sister Temima Suleman. They have been with me at the time of my happiness and terrible throughout my study!

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Table of Contents

List of tables

List of figures

Abstract

Antenatal care visit is the service given to pregnant women in order to have a safe pregnancy and a healthy baby. Recently the technical working group of World Health Organization has recommended a minimum level of care to be eight visits throughout the pregnancy to reduce the maternal morbidity and mortality. The main objectives of this study was assessing the regional variation of number of ANC service visits per woman and identifying the factors influencing number of antenatal care visits based on 2016 EDHS dataset. The survey collected information from a total of 15,683 women aged 15-49 years out of which 7174 women were considered in this study. Multilevel count regression models were used to explore the major risk factors and regional differentials in number of antenatal care service visits per a child bearing woman in Ethiopia. Descriptive statistics results show that nationally about 2481(35%) of mothers did not take any antenatal care, which indicates excess zero and less percentage of non-zero counts and only 255(3.6%) attended ANC service follow-up eight times and above. From several multilevel count regression models (Poisson, NB, ZIP, ZINB, HP, HNB), multilevel hurdle Poisson model was selected using model comparison criteria like AIC, BIC and Deviance. Among multilevel hurdle regression models (null model, random intercept with fixed coefficient and random coefficient model), it was found that the random intercept with fixed coefficient model is the best model to describe the data set. At the stage of multilevel, HP model showed that predictor variables age, type of place of residence, wealth index, Mother educational level, husband educational level, frequency of watching television, distance from health facility, wantedness of pregnancy and pregnancy complication were found to be related with the antenatal care service follow-up. The multilevel analysis further showed that there are within and between regional variations per mother regarding to ANC service visits in Ethiopia. The findings of this study might help in planning and developing strategies for utilization of ANC visits among pregnant women in Ethiopia.

Keywords: ANC; count regression; excessive zeros; over dispersion; multilevel count regression.

Acronyms

AIC	Akaki-Information Criteria
ANC	Antenatal Care
ANOVA	Analysis of Variance
BIC	Bayesian Information Criteria
CSA	Central Statistics Agency
EA	Enumeration Areas
EDHS	Ethiopian Demographic Health Survey
EPHI	Ethiopian Public Health Institute
FMoH	Federal Ministry of Health
GLM	Generalized Linear Model
HP	Hurdle poisson
HEP	Health Extension Program
HNB	Hurdle Negative Binomial
MLE	Maximum Likelihood Estimation
MoH	Ministry of Health
ICC	Intra Class Correlation
MMR	Maternal Mortality Rate
NB	Negative Binomial
STI	Sexually Transmitted Infection
TB	Tuberculosis
UN	United Nation
UNFPA	United Nations Population Fund
WHO	World Health Organization
ZINB	Zero Inflated Negative Binomial
ZIP	Zero Inflated Poisson

Chapter One

1 Introduction

1.1 Back ground of the study

Antenatal care (ANC) refers to the regular medical and nursing care recommended for women during pregnancy (Catling et al., 2015). ANC is a type of preventive care with the goal of providing regular check-ups that permit doctors or midwives to treat and prevent potential health problems throughout the course of the pregnancy while promoting healthy lifestyles that benefit both mother and child (Atuyambe et al., 2008). It is a care before birth for pregnant women and includes education, counseling, screening and treatment to monitor and to promote the well - being of the mother and fetus.

However, Antenatal Care have such attractive benefits and strategies, according to the every year, at least half a million women and girls die as a result of complications during pregnancy, childbirth or the six weeks following delivery and almost all (99%) of these deaths occur in developing countries. This shows that the Antenatal care activity is very weak in developing country (Ojo, 2004; WHO , 2007).

Now a days, 71% of women worldwide receive any ANC services; in industrialized countries, more than 95% of pregnant women have access to ANC. In sub-Saharan Africa, 69% of pregnant women have at least one ANC visit (Nishat F, 2010). While different studies have looked at diverse risk factors for antenatal care (ANC) and delivery service utilization in the country, MoH of Ethiopia in 2007 reported that about 52% Ethiopian women received one or more ANC visits, less than 17% received professionally assisted delivery care and 19% received postnatal care (Ministry of Health ,2006).

In most countries, the greatest proportionate difference occurs between women following socioeconomic, demographic, health and environmental related factors (Edward N., Bernardin S. and Eric A., 2012). In Metekel zone, Northwest Ethiopia, 49.8% of pregnant women had received at least one antenatal care visit during the pregnancy of their last delivery (Gurmesa T., 2009). According to the study report, lack of awareness, low educational status and socio-economic characteristics, place of residence, educational status, husband's educational status, possessing radio, monthly income and knowledge about antenatal care were found to have a statistically significant reasons mentioned for not attending antenatal care utilization in the zone (Gurmesa T., 2009). A study conducted in South western Ethiopia in 2009 (Bahilu T, et al. ,March 2009) showed that 28.5% of pregnant women in Yem Special Woreda received ANC at least once but the majority 71.5% reported that they did not attend ANC up to their last pregnancy.

Thus, the above information indicates that, studies in different areas are still very varied and limited due to different factors. That is why this study was aimed to statistically analyze the determinants of the barriers in number of antenatal care service visits among pregnant women in Ethiopia. Furthermore, this study provided valuable information about count data models when the assumption of the standard Poisson regression is violated (when there is greater variability in the response counts than one would expect if the response distribution truly were Poisson). According to some study, the negative binomial and ZIP model appears to be superior when the event -stage distribution is positive and when there is moderate to moderately-high zero-inflation but not extreme zero –inflation (Gurmu, S. and P.K. Trivedi, 1996; Md Abdullah al Mamun, 2014)

In this study, we tried to assess Socio-demographic, Fertility related characteristics and ANC service related determinants of completing the recommended ANC visits among pregnant women of reproductive age in Ethiopia by considering the clustered nature of the data. In order to address this objective, recent data from a large-scale household survey conducted in 2016 provided a valuable opportunity. The analysis of determinants allowed us a better identification of women who didn’t utilize ANC services eight or more (the 2016 WHO Antenatal Care Recommendation) times with a high probability; as a result more effective and efficient application of interventions was held. In such occasions, it was of interest to examine the applicability of Multilevel count regression models such as multilevel ZIP, multilevel ZINB, multilevel HP and multilevel HNB in addition to NB and Poisson regression models and compare their performances in terms of their goodness-of-fit statistics, AIC, BIC, likelihood ratio test and theoretical soundness.

1.2 Statements of the problem

Antenatal Care (ANC) is a type of care given for women during pregnancy and it is one of the bases of maternal health service. The major goals are Health promotion and disease prevention, early detection and treatment of complications and existing diseases, birth preparedness and complication readiness planning (WHO, 2002)

But number of studies have identified the lack of antenatal care as a risk factor for maternal morbidity and mortality (Thorsten V, et al, 2015). In 2015, an estimated 303,000 women died as a result of pregnancy and childbirth-related complication worldwide. Developing countries accounted for about 99% of global maternal deaths, with the maternal mortality ratio (MMR) of 239 per 100,000 live births. Despite an apparent global improvement made over the last two and half decades, the worldwide MM dropped by about 45% in 2015 which is far from the decline targeted (75%) to be achieved by 2015(WHO, 2015). Ethiopia as one of the sub-Sahara country, maternal care is very poor. According to EDHS 2011 and 2016 only 34% and 62 % of women who gave birth in the five years preceding the survey received antenatal care from a skilled provider respectively one woman in every five (19%) made four or more antenatal care visits during the course of her pregnancy(EDHS, 2016).

Since inadequate ANC is associated with worse pregnancy outcomes, it is vital for health policy makers to better understand the factors influencing proper and prompt utilization of ANC. Even though, different studies have highlighted many factors affecting the use of antenatal care in different contexts, these findings have not been synthesized collectively **(**Ali SA et al., 2018). Therefore, there was a need to carry out a study to synthesize findings regarding the factors affecting the utilization of number of ANC visits. Hence the objective of this study was to assess the factors affecting utilization of number of ANC visits among pregnant women in Ethiopia.

Usage of antenatal care services has been studied using the binary logistic model; classifying women into whether or not they had the minimum four attendants during pregnancy as prescribed by the World Health Organization (Navaneetham and Dharmalingam, 2002; Magadi et al., 2007; Habibov, 2011). However, the number of times women attend antenatal clinic is a count variable which naturally should be explored assuming appropriate count models such as the Poison log-linear or negative binomial model. Thus, binary logistic regression undercounts the total number of ANC Visits, since multiple number ANC service visits are collapsed into a single unit to fulfill the requirements of binary logistic regression. Besides, binary logistic regression cannot provide sufficient information for studying the pattern of multiple ANC visits that means it merely predicts a mother is using the service minimum of four or not rather than the number of ANC service visits.

Most of those researches are done on small-scale survey data which were came from only certain regions of the country. Utilization of antenatal care services measured by the number of visits is a count variable and, for most developing countries, it is often characterized with excessive zeros due to nonattendance, and over dispersion necessitating the use of special count models for analysis. In this case, two states may be assumed to better reflect the situation. One of the states is the structural zero (or zero count) state where the only counts are zeros. The other state is the sampling zero state where the counts could be zeros or values greater than zero.

Therefore, this study was conducted to fill the problem addressed above using multilevel Poisson, multilevel NB, multilevel zero-inflated Poisson (multilevel ZIP), multilevel zero inflated negative binomial (multilevel ZINB), multilevel Hurdle Poisson(multilevel HP) and multilevel Hurdle negative binomial(multilevel HNB) regression models for the data and select best fitted count regression model for the data set EDH 2016. In this regard, the research questions of the interest were:

1) What are determinant risk factors that affect the number of ANC visit attendances in Ethiopia?
2) Is there between and within regional variations regarding to the number of ANC service visits in Ethiopia?
3) Which count regression model is better to analyze number of ANC service Visits for the dataset 2016 EDHS?

1.3 Objectives of the Study

1.3.1 General objective:

To assess factors influencing number of attendances for antenatal care visits among pregnant women in Ethiopia.

1.3.2 Specific objectives

1) To identify determinant risk factors of ANC visits in Ethiopia.
2) To examine between and within regional variation of number of ANC service visits among pregnant women in Ethiopia.
3) To explore multilevel count regression models on ANC follow ups from the dataset.

1.4 Significance of the study

The primary beneficiaries of the findings of this study will be all fertile aged mothers not utilizing antenatal care services in different parts of Ethiopia. This will lead to improve pregnancies, delivery and postpartum outcomes. It will also provide a systematic body of knowledge that can be explored for appropriate policy formulation, act as a reminder to both the state and civil society to always incorporate reproductive health needs of pregnant women. Effective level of utilization of ANC services, through early ANC attendance, receiving health promotion information and health care is crucial to improving maternal and fetal health during pregnancy and reducing morbidity and mortality rates. The findings will assist in coming up with policies for improving the level of utilization of ANC services visits by larger percent of fertile women across all regions in Ethiopia.

1.5 Limitations of the Study

In this study, there were some challenges that the researcher faced. One of the potential limitations of this study is the cross-sectional nature of our analysis. The study uses reported characteristics of mothers that may vary within time. The study used data from national surveys that have inherent gaps such as absence of some variables that may affect the response variable and some variables are not included because of large number of missing values like parity.

Chapter Two

2 Literature Review

This chapter presents a review of the literature on determinants of ANC visits. The chapter is based on antenatal care visit utilization studies conducted in various countries including in Ethiopia.

2.1 Literature Review on ANC

Antenatal care is the care given to pregnant women so that they have safe pregnancy and healthy baby (Abosse Z, W. M.,2010). The provision of antenatal care (ANC) services brings with it a positive impact on pregnancy as it enables the identification of risk factors and early diagnosis of pregnancy complications like preterm delivery and appropriate management (Perumal N, C. D., 2013). The positive effect can be realized through screening for pregnancy problems, evaluating pregnancy risk, treating difficulties that may arise during the antenatal period, giving treatment that may improve pregnancy outcomes, providing information to the pregnant woman, preparing physically and psychologically for childbirth and parenthood (Kisuule I, K. D.,2013)

Generally, at the first antenatal care service visit to a healthcare facility, a pregnant lady is issued with an antenatal care card. This card is the fundamental record of the pregnancy and is filled in whenever the woman goes for an ANC service visit. After the first visit, the woman is considered to be booked for successive ANC visits to identify the complications like preterm delivery and manage these complications in timely manner (Finlayson K, D. S.., 2013).

2.2 Global Perspective of Antenatal Care

Antenatal care has long been considered a basic component of any reproductive health care program. Different models of antenatal care have been put into practice all over the world (Banda, 2013). These models are the result of factors such as socio-cultural, historical, traditional nature as well as economy of the particular country. Moreover, human and financial resources of the specific health system substantially play a part in building the model (Shah & Say, 2007). Most developed countries use traditional model of prenatal care which is based on larger number of visits, approximately 7-10 visits. They include starting antenatal as early as possible, monthly visits up to 28 weeks, followed by weekly up to 36 weeks until delivery, (Say & Raine, 2007). Pregnant women in these high income countries receive adequate prenatal care which includes frequent tests, and ultra sound evaluation. They also give birth under supervision of medically trained personnel and have prompt access to emergency treatment if complications arise (Chaibva C. N., 2009). Child mortality increases, to an important extent, with births to very young or to very old mothers. Several studies from a variety of countries, relating maternal age to various aspects of pregnancy and child development, suggest that maternal age is a central variable influencing pregnancy outcome (Rosenfeld, 2009). Roughly one third of all the women ages 20-24 in 10 of 11 Latin American countries, and half in Guatemala, have their first child before their 20th birthday (Erickson, 1998).

A retrospective observational study conducted by Nisar and White in far North Queensland Australia examined reasons for women not accessing antenatal care and subsequent pregnancy outcomes. The study revealed that women who did not access 10 antenatal care were more likely to be highly parlous or young. The same group were more indigenous and users of alcohol than those who accessed antenatal care (Nisar & White, 2003). Another study on the effectiveness of antenatal care on birth weight in Mexico found that women who received poor antenatal care had a 76 percent excess risk of low birth weight associated with premature delivery compared to those who received adequate antenatal care (Notzon, 2015).

2.3 Utilization of ANC services

Antenatal care allows for the management of pregnancy, detection and treatment of complications and promotion of good health (D'Alton & Miller, 2015). According to Kasabiiti jennifer Asiimwe, (Kasabiiti, 2007) in western Uganda the ability of a woman to afford antenatal care (ANC) services has a significant association to the number of ANC visits she is likely to make. This resonates with studies elsewhere that women having to take transport to ANC facility, high fees for necessary but costly laboratory fees, drugs and consultation fees in case of private centers not serviced by government hospitals are deterrence to the level of utilization of maternal services as highlighted by (Atuyambe et al., 2008). Although in their study, there was no significant relationship between affordability and level of utilization of antenatal care, these associations indicates the unwillingness by mothers to pay for ANC services. A study by Friedman and others (Susan Hatters Friedman, 2009) among 211 women with no prenatal care identified the primary reasons as follows: 30% had problems with substance use; 29% experienced denial of pregnancy, 18% had financial reasons, 9% concealed pregnancy and 6% believed they did not need prenatal care due to multi parity. Women with substance use disorders were significantly more likely to be older, unemployed multi-gravidas.

According to study done by Birmeta and others in Holeta town Ethiopia, (Birmeta et al., 2013), among 422 women who had given birth in the past three years prior to the survey, 87% of the women had at least one antenatal visit during their last pregnancy. Among the antenatal service users, 33.7% had less than four antenatal visits. More than half of the antenatal care (ANC) attendants made their first visit during their second and third trimester of pregnancy although WHO recommended ANC should be started at the first trimester of the pregnancy. This study also revealed that there was a significant association ($P<0.05$) between ANC attendance and some demographic, socio-economic and health related factors (age at last birth, literacy status of women, average monthly family income, media exposure, attitude towards pregnancy, knowledge on danger signs of pregnancy and presence of husband approval on ANC).

2.3.1 Factors associated with utilization of antenatal care

Many factors influence late initiation or poor ANC. Some of the identified factors contributing to late ANC include: un availability of services, cost of services, lack of media exposure, low social economic status and others (Simkhada et al., 2008).

The ability to utilize ANC services in developing countries is affected by a number of factors (Mpembeni R et al, 2010 and Farah S et al 2016). According to Andersen and Newman's health behavioral model (Boerleider AW et al 2013). (Figure 2.1), individual determinants of health care utilization can be divided into predisposing, enabling and need components (Beeckman K et al., 2013; Baarveld F, et al., 2012). This model helped us to conceptualize the factors associated with utilization of ANC visit attendances and was also used to do the focused literature search in order to find out the factors related with antenatal care utilization for this review.

With respect to ANC visits, influencing determinants refer to individual characteristics which exist prior to the pregnancy and affect the tendency to use care. Last studies have concluded that young age, low educational level, lack of a paid job, poor language proficiency, support from a social network and lack of knowledge of the health care system are related with inadequate ANC utilization (Baarveld F et al., 2012; Kingston D et al., 2013). Enabling determinants refer to conditions which make ANC available to pregnant women. The absence of health insurance, the planned pattern of ANC, hospital type at booking, personalized communication, and knowledge of cultural practices of the care provider have been found to be associated with inadequate ANC services utilization (Putman K et al., 2013; Baarveld F, et al., 2012). The pregnancy-need components of the determinants include pregnancy-related elements explaining the degree of care needed (Baarveld F, et al., 2012; Kingston D, et al., 2013). Insufficient use of antenatal care seems to be associated to high parity, unplanned pregnancy, no previous premature birth, discontinuity of care, late recognition of pregnancy and behavioral factors such as smoking during pregnancy (Baarveld F, et al., 2012; Kingston D, et al., 2013). Some of the important predictors are discussed below in detail

2.3.1.1Maternal age

Maternal age has been shown to both negatively and positively influence utilization of ANC in general. Younger women may be less likely to use either antenatal care or delivery care, or to have their infants immunized. According to (Adamu & Salihu, 2002), delay in seeking care, in reaching adequate health facilities, and in receiving appropriate care at facilities is a well-known barrier to care for all women. This may be especially pronounced for young women, who may have little knowledge and experience in seeking care.

According to Mlilo-Chaibva, (Chaibva, 2009) a woman's age might influence her decision to initiate ANC late or not to attend ANC at all. She claimed that pregnant adolescents might tend to hide their pregnancies because they might be unmarried, attending school, afraid of or prejudicial against health care providers or they might be simply too young and ignorant to appreciate the value of ANC. A study conducted in Turkey demonstrated that teenage mothers were statistically less likely to use ANC services (Ciceklioglu, Soyer, & Ocek, 2005). However, in other studies teenage mothers were more likely to start utilizing ANC services earlier than their older counter parts (Banda, 2013).

Outcomes from various studies have found mixed evidence of an association between age and utilization of ANC service visits. In some studies, young age of women has been identified as influencing determinant for utilization of ANC services visits (Nketiah-Amponsah E et al., 2013). However, few studies suggest contrary to these studies, few studies suggest that increased age is associated with more utilization of ANC services (Singh SK et al., 2013). For example, study from Central Ethiopia found that the odds of attending ANC are 1.2 times higher (OR=1.168) for women in the age group of 20-34 as compared to those in the age group 15–19 women (Birmeta K et al, 2013). Likewise, a study conducted in Vietnam found that older women (more than 25 years old) were more likely to utilize antenatal care (Tran TK et al., 2012). Similarly, a study conducted in China also found that women between the ages of 25 and 30 and women older than 30 were more likely to have adequately utilized antenatal care (AOR=2.2 and 1.9, 95%CI=1.4-3.5 and 1.1-3.2, respectively) than younger women (Yang S, et al., 2012).

2.3.1.2Women's education

Maternal education has also been shown to influence utilization of ANC. Matsumura and Gubhaju study (Matsumura & Gubhaju, 2001) conducted in Nepal demonstrated that women with higher education were more likely to utilize ANC than those with lower education. A study carried out by Pallikadavath and others (Pallikadavath, Foss, & Stones, 2004) found similar results, in their study they had demonstrated that both maternal and paternal education positively influence utilization of ANC.

Moreover, higher levels of education tend to positively affect health-seeking behaviors, and education may increase a woman's control over her pregnancy (Zhao QZJH et al., 2012). In addition, education may help to expose women to more health education messages and campaigns, enabling them to recognize danger signs and complications and take appropriate action (Zhao QZJH et al., 2012). These women might have greater opportunities to receive health information and pay more attention to maternal healthcare (Zhao QZJH et al., 2012). Studies have shown that women with lower education usually have less knowledge about ANC services and more difficulties to get access to ANC services (Tran TK et al, 2012). A study done in Central Ethiopia found that women with some education were more than twice more likely to attend ANC (OR=2.645) as compared with those who had no education (Birmeta K et al, 2013).

2.3.1.3Economic Factors

Poverty exacerbates the problem of low birth weight for the less fortunate have both nutritional and inadequate access to food during pregnancy (Gitonga, 2007). Social economic disadvantage may lead to adverse psychological, behavioural or otherw environmental exposures that restrict foetal growth (Bhargava, 2009). Limited economic power may be an impediment in seeking ANC services among pregnant adolescents, since most of them might be school going and financially dependent on parents, spouses or boyfriends and might be unable to afford ANC fees and the basic requirements for delivery in a hospital (Chaibva, 2009). According to Hadi (Abdullahel Hadi,

2007) in their research on “The inaccessibility and utilization of antenatal health care services in Balkh Province of Afghanistan”, the utilization of Antenatal care (ANC) services was differentiated by the participation of women in activities. The use of each of the ANC services was significantly lower among women who were involved in economic activities than among those not economically active.

Financial difficulties have been considered as an important barrier to antenatal care for migrant women (Zhao QZJH et al., 2012). Most of the studies have shown a positive association between socioeconomic status and the utilization of ANC (Efendi F et al., 2016). A study from Ethiopia identified that when women with higher incomes tend to start ANC early and the likelihood of utilizing ANC decreased, as the family income gets lower (Birmeta K et al, 2013). Similarly, a study from China found that women who had higher household income were more likely to have sufficiently utilized ANC services (AOR=1.6, 95% CI=1.0-2.5) (Zhao QZJH, Yang S, Pan J, et al., 2012). The positive contribution of better wealth status for all maternity service indicators and its significant contribution to postnatal care are also observed in other studies (Worku AG et al., 2013).

2.3.1.4Parity

Studies have suggested that parity influences initiation of ANC, as parity increases, the experience of timely initiation of ANC decreases (Tran TK et al., 2012). High parity women might tend to rely on their experiences from previous pregnancies and not feel the need for antenatal care (Zhao QZJH et al., 2012). Due to their greater level of experience, these women might feel more confident during pregnancy and consider antenatal care to be less important (Zhao QZJH et al., 2012). This was evidenced by findings in different studies in which respondents with first pregnancy were about two times more likely to book early than those with more children (Gross K et al., 2012).

2.3.1.5History of reproductive loss and previous pregnancy complications

A history of reproductive loss has proved to be a strong predictor of early ANC initiation (Gross K et al., 2012). The researchers determined that women who had previously experienced miscarriages or stillbirths are more likely to utilize ANC services as compared to their counterparts (Zhao QZJH et al., 2012)

2.3.1.6Supportive spouse or partner

Having a spouse or partner who is not supportive was reported to be associated with initiating ANC late for both adolescents and adult women (p=0.035) (Gross K et al., 2012). In of the studies, the researchers concluded that women who had no support from their partners utilized ANC services almost three weeks later than those who were given support (Gross K et al., 2012).

Similarly, the utilization of antenatal care service visits was almost nine times more likely for women reported their husbands to approve ANC than women with those whose husbands did not approve ANC service visit (OR=8.99) (Rosliza A et al 2011)

2.3.1.7Women's knowledge of antenatal care

Knowledge on ANC is critical in determining pregnant women's use of antenatal services (Simkhada et al., 2008). Moreover, studies have shown that adequate knowledge of ANC has a positive and statistically significant effect (Banda, 2013).

Health knowledge is an important factor. It enables women to be aware of their rights and health status in order to seek appropriate health services (Onasoga OA et al., 2012). The odds of utilizing ANC were more than three times for those with better knowledge of danger signs of pregnancy than those with poor knowledge (OR=3.541) (Birmeta K et al 2013). The studies have revealed that sufficient knowledge of the benefits of ANC and of the complications associated with pregnancy plays an important role in the utilization of ANC services. In of the studies conducted by Rosliza and Muhamad, no significant relationship (p=0.279) was found between knowledge of ANC and early antenatal booking (Ali NR et al, 1999). They discovered that pregnant women's level of knowledge of the importance of ANC, screening tests, and complications of diabetes and hypertension during pregnancy was poor (Rosliza A et al., 2011).

2.3.1.8Quality of care

In the study conducted in Nigeria by Amosu (Amosu et al., 2011) the findings indicated that health care provider and pregnant women ignorance about ANC was one of the factors affecting utilization of ANC. To ensure women accesses quality care adequate number of trained health workers, sufficient equipment and supplies; and adequate referral or reliable transportation to a hospital or other health facilities in the event of an emergency (Banchani & Tenkorang, 2014). Studies clearly indicate that countries with high maternal, perinatal and neonatal mortality have inadequate and poor quality health service, which can be associated with reduced utilization of health service. Reference on these studies show that the use of evidence-based guidelines leads to better process and outcomes of health, when appropriately implemented. Emphasis is therefore placed on the use of standards of care as a way of addressing barriers to quality care (WHO, 2007). Improving quality of care for clients means understanding their cultural values, previous experiences and perceptions and the role of the health system (Saha, Beach, & Cooper, 2008). Patient-centered care is not limited to communication and often focuses on other aspects of care such as convenience of office hours, ability to get appointments when needed, being seen on time for appointments and having services near one's place of residence (Saha et al., 2008).

Women were reported to initiate ANC late owing to the perceived bad quality of service at the healthcare facility (Gross K et al, 2012). The women's criticisms were associated mainly to lack of services, citing reasons such as being sent home without receiving services due to insufficient staff, and having to purchase drugs, cards or diagnostic tests, although the service was supposed to be free (Gross K et al, 2012). Another strong facility level factor for skilled maternal care utilization was the performance of health facilities. The presence of all the six signal functions in the nearby basic needed obstetric care facility (health center) positively contributes to the utilization of all indicators of skilled maternal services. Functioning obstetric facility means performing the necessary services for normal situations and complications and these services should be available 24 hours a day and 7 days a week. The presence of all signal functions shows better performance (quality) of a health facility (Worku AG et al 2013).

2.3.1.9Distance to a healthcare facility

Distance to the health facility is inversely associated with ANC utilization (Glei et al., 2003a). A study conducted by Magadi (Magadi et al., 2004) in Kenya demonstrated that an increase in distance to the nearest healthcare facilities was associated with fewer antenatal visits. Moreover, uncomfortable transport, poor road conditions and difficulties in crossing big rivers have also been shown to be barriers to utilization of ANC in studies conducted in Zimbabwe (Mathole, Lindmark, Majoko, & Ahlberg, 2004) and in Pakistan (Mumtaz & Salway, 2005).

Generally, the effect of distance on the use of services increases when it is combined with lack of transportation particularly in developing countries (Ali NR et al 1999). Moreover, access to the facilities also has an effect on the frequencies of services being used (Ali NR et al., 1999). Studies from Pakistan have found that access to obstetric care depends upon the transportation system and physical distance between the villages and the centers (Midhet F et al., 1998). Moreover, with huge expenditures and passage of twenty-two years, only 33% of the rural Pakistani population is living within access of 5 kilometers (km) (World Health Organization, 2007). This distance has even been found as a hindrance in seeking care especially in the case of women who lacks autonomy and needs somebody to accompany her (Shaikh BT, Hatcher J., 2005). As a result, the factor of distance gets strongly adhered to other factors such as the availability of transport, the total cost of travel and women's restricted mobility (Shaikh BT, Hatcher J., 2005). Likewise, other studies have also found that an increase in distance to the nearest health facility led to fewer antenatal visits (Nicholas NA et al 2012). A strong association between distance to the health facility and utilization of ANC services was reported by another study (Onasoga OA et al., 2012). In trying to explain the association, the researchers argue that many pregnant women find it distressing to walk long distances or take two or more taxis to a health facility; therefore, they tend to utilize ANC services less regularly than those who live close by (Onasoga OA et al., 2012).

2.3.1.10 High ANC Fees

According to the World Health Organization (WHO), the cost of providing basic maternal and newborn health services in developing countries averages about US$3 per person (Gilbert, Patel, Farmer, & Lu, 2015). The perceived high fees might influence some pregnant women, including adolescents, to resort to the services of traditional birth attendants (TBAs), which are cheaper and can be paid in kind (Ikamari, 2004). This has serious implications for the pregnant adolescents' health. Home care and home deliveries without ANC may contribute to poorer pregnancy outcomes for the adolescent mother and her baby. Many pregnant adolescents depend on spouses and/or parents and are unlikely to have health insurance to cover the health care costs. Reynolds and others cite socio-economic factors as contributing to poor ANC attendance and thus also to poor maternal and neonatal outcomes (Reynolds, Wong, & Tucker, 2006). Studies by Fatusi and Chiwunzie (Osubor, Fatusi, & Chiwuzie, 2006), revealed that clients are usually prepared to overcome barriers such as high user fees if they are satisfied with the quality of care rendered and if the human and material resources are available.

2.4 Literatures on count regression models

Models for count data have been prominent in many branches of the recent applied literature, for example, in health economics (e.g., in numbers of visits to health facilities) management (e.g., numbers of patents) and industrial organization (e.g., numbers of entrants to markets). The foundational building block in this modeling framework is the Poisson regression model. But, because of its implicit restriction on the distribution of observed counts – in the Poisson model, the variance of the random variable is constrained to equal the mean – researchers routinely employ more general specifications, usually the negative binomial (NB) model which is the standard choice for a basic count data model. This excess variation may occur incorrect inference about parameter estimates, standard errors, tests and confidence intervals. Over dispersion frequently arises for various reasons, including mechanisms that generate excessive zero counts or censoring. As a result over-dispersed count data are common in many areas which in turn, have led to the development of statistical methodology for modeling over dispersed data (Sellers and Shmueli, 2013). The negative binomial distribution looks like the Poisson distribution, but with a longer, fatter tail to the extent that the variance exceeds the mean. As a result over-dispersed count data are common in many areas which in turn, have led to the development of statistical methodology for modeling over dispersed data (Sellers and Shmueli, 2013). The negative binomial distribution looks like the Poisson distribution, but with a longer, fatter tail to the extent that the variance exceeds the mean. Depending on the degree of over dispersion, the negative binomial model can capture (much) more zeros than the Poisson model (Hilbe, 2011).

However, the model may still be insufficient in many empirical applications with a clear stack of zero values in the data. Zero inflated models provide a way of modeling the excessive proportion of zero values and allow for over dispersion. Especially when there is a large number of zeros, these techniques are much better able to provide a good fit than Poisson or negative binomial models (Lambert, 1992). There are also many applications that extend the Poisson and NB models to accommodate special features of the data generating process, such as zero inflation. The basic models for fixed and random effects have also been extended to the Poisson and NB models for counts (Greene, 2007).

There have, however, been scores of further refinements and extensions that are documented in a huge literature and several book length treatments such as (Cameron A.C. and Trivedi P.K., 2005). The multilevel regression model has become known in the research literature under a variety of names, such as ‘random coefficient model’, ‘variance component model’, and ‘hierarchical linear model’. Statistically oriented publications tend to refer to the model as a mixed-effects or mixed model. The multilevel count regression models assume that there is a hierarchical data set, with one single outcome or response variable that is measured at the lowest level, and explanatory variables at all existing levels. Conceptually, it is useful to view the multilevel regression model as a hierarchical system of regression equations (Joop, 2010).

Models for continuous data such as linear regression and Analysis of Variance (ANOVA) should not be directly applied to discrete response variables due to the underlying distributional assumptions required by these models for their correct application. Generalized linear models (GLMs) use a regression procedure to fit relationships between predictor and dependent variables. Unlike classical regression model where the random component (i.e., the error term) is assumed to follow a normal distribution, the random component in a GLM is assumed to follow an exponential family of distributions. In this section, several common features of skewed discrete random variables related to over-dispersion and zero-inflation are included. Over dispersion occurs where there is greater variability in a dataset than expected under a standard statistical model (normally Poisson), i.e. the variance in a dataset is greater than the mean (McElduff, 2012; Akbarzadeh et al., 2013). The presence of over dispersion in discrete data causes summary statistics resulting from a simple statistical model to be larger than anticipated and can lead to incorrect inferences under such a simple hypothesis (Gupta et al., 2013). Even though there are several statistical models, some models may not be appropriate to deal with some specific types of data. Their use is solely depending on the types and nature of the data. In this study, the form of response variable is a count data, which is most often characterized as non-normal distribution.

Many kinds of data, including observational data collected in the human and biological sciences, have a hierarchical or clustered structure. For example, animal and human studies of inheritance deal with a natural hierarchy where offspring are grouped within families. Offspring from the same parents tend to be more alike in their physical and mental characteristics than individuals chosen at random from the population at large. We prefer to a hierarchy as consisting of units grouped at different levels (Goldstein, 1999).

Thus, to deal with the data and methodological issues related with modeling the number of ANC visits, a wide variety of statistical methods can be used. There are count regression models which had been developed to analyze data with count response variables. In this study, count regression models with two levels were used in the analysis to the dataset. The relative importance of these predictive variables of ANC visit may vary depending on the prevailing socio-economic conditions in a community.

Chapter Three

3 Data and Methodology

3.1 Source of data

This study utilizes the 2016 Ethiopian Demographic and Health survey (EDHS) data. The 2016 Ethiopia Demographic and Health Survey (EDHS) was the fourth survey implemented by the Central Statistical Agency (CSA). The CSA has conducted the survey in collaboration with the Federal Ministry of Health (FMoH) and the Ethiopian Public Health Institute (EPHI) with technical assistance from ICF International, and financial as well as technical support from development partners. The survey was conducted from January 18, 2016, to June 27, 2016, based on a nationally representative sample that provides estimates at the national and regional levels and for urban and rural areas based on the 2007 Ethiopian population and housing census using a probability proportional to size selection. The detailed reports of the data handling are available from the full report of the EDHS 2016(EDHS, 2016). A total of 18,008 households were selected for the sample, of which 17,067 were occupied, of the occupied households, 16,650 were successfully interviewed, yielding a response rate of 98 percent.

The EDHS 2016 followed a complex sampling design (i.e. combined stratified and cluster in two stages, with unequal probabilities of selection that result in weighted sample to separate the sample components) and was designed in order to obtain representative estimates at the national, and regional level (administratively, the country is divided into nine geographical regions and 2 administrative cities).

The strata considered in the survey were at the regional and residence levels. In the first stage, a total of 645 enumeration areas (EAs) (202 in urban areas and 443 in rural areas) were selected with probability proportional to EA size (based on the 2007 population census) and with independent selection in each sampling stratum. A household listing operation was carried out in all of the selected EAs from September to December 2015. The resulting lists of households served as a sampling frame for the selection of households in the second stage. In the second stage of selection, a fixed number of 28 households per cluster were selected with an equal probability systematic selection from the newly created household listing.

In all of the selected households, the survey target groups are children age 0-59 months, women aged 15-49 and men age 15-59 who were either permanent residents of the selected households or visitors who stayed in the household the night before the survey were included.

From the women questioner, there were total of 16,583 eligible (15-49 aged) women and among them, 15683 Women were interviewed with response rate of 95%. From 15,683 Women who were interviewed, only 7174 had given information about antenatal care service visits. Therefore, in this study, all 7174 women who were experienced to ANC were considered to determine factors that affect number of ANC service visits.

The response variable of this study was the number of antenatal care visits of pregnant women from early pregnancy to their 9 months of pregnancy period. Thus, this study tried to include socioeconomic, demographic, fertility and ANC service related factors that are assumed as a potential determinants for the barriers in the number of antenatal care service visits, adopted from literature reviews and their theoretical justification. Detailed descriptions of these factors are listed below.

3.2 Variables included in the study

Depending on the demonstrated related literature reviews, the variables included in this study are listed as follows.

3.2.1 Response variable

The response variable of this study is denoted by Y_{ij} which indicates the number of antenatal care visits per pregnant women in Ethiopia. Thus, Y_{ij} takes on values 0, 1, 2 … Where i denotes the individual pregnant woman and j is the region in which the pregnant mothers belongs to.

3.2.2 Explanatory variables

The predictor factors that was assessed as the main determinants against attending Antenatal care follow up in this study are described as follows.

- Socio-demographic characteristics: This included maternal age, region, Husbands educational level, mother's educational level, place of residence (urban-rural), wealth index and frequency of watching television.
- Fertility related characteristics: This included pregnancy complication.

- ANC service-related characteristics: this included Distance to a healthcare facility, wantedness of pregnancy, peer influence and parents supporting the mother.

Table 3.1 Detailed description of Socio-demographic, Fertility related, ANC service-related variables regarding to antenatal care visit service utilization are presented as follows.

Description and Name	Categories	Description and Name	Categories
maternal age (Agec)	1=15-19	educational level of mother(ELM)	0=No education
	2=20-24		1=Primary
	3=25-29		2=Secondary
	4=30-34		3= Higher
	5=35-39	place of residence(PResi)	1=Urban
	6=40-44		2=Rural
	7=45-49	wealth index(WI)	1=Poorest
region(Region)	1=Tigray		2= Poorer
	2=Afar		3= Middle
	3=Amhara		4= Richer
	4=Oromia		5=Richest
	5=Somali	pregnancy complication(pregnancy)	0=No
	6=Benishangul		1=Yes
	7=SNNPR	Frequency of watching television(FWT)	0=Not at all
	8=Gambela		1= Less than once a week
	9=Harari		2=At least once a week
	10=Addis Adaba	wantedness of pregnancy(WP)	1=Then
	11=Dire Dawa		2=Later
Husbands educational level(HusbandEL)	0=No education		3=No more
	1=Primary	peer influence (peerInfluence)	0=No problem
	2=Secondary		1=Big problem
	3=Higher		2=Not a big problem
Distance to a healthcare facility(Distance)	0=No problem	parents supporting the mother(supportivepar)	0=No problem
	1=Big problem		1=Big problem
	2=Not a big problem		2=Not a big problem

3.3 Methodology

Poisson distribution is the most common probability model for discrete data with observations assumed to have a constant rate of occurrence amongst individual units with the property of equal mean and variance. However, in many applications the variance is greater than the mean and over-dispersion is said to be present. The application of the Poisson distribution to data exhibiting over-dispersion can lead to incorrect inferences and/or inefficient analyses. The most commonly used extension of the Poisson distribution is the negative binomial distribution which allows for unequal mean and variance but may still be inadequate to model datasets with long tails and/or value-inflation (Wondewosen et al., 2014; Ayati and Abbasi, 2014; Sileshi, 2007 and Loquiha et al., 2013).

In this study, count regression models such as Poisson, negative binomial, zero-inflated Poisson regression, and zero-inflated negative binomial regression models, hurdle Poisson model and hurdle negative binomial models were applied. Further multilevel count regression models like multilevel Poisson, multilevel NB, multilevel ZIP, multilevel hurdle Poisson model and, multilevel hurdle negative binomial models were used to check variation among the regions.

3.3.1 Single level count regression models

3.3.1.1 Poisson regression model

The Poisson distribution is the most common probability distribution for count data. The Poisson probability model is appropriate for events that occur randomly over time and/or space. Given that the dependent variable (number of ANC visits) is a non-negative integer; most of the recent thinking in the field is the use Poisson regression model as a starting point. In a standard Poisson regression model, the probability of pregnant women having antenatal care service visits until her nine (9) months of pregnancy period (where is a non-negative integer) is given by:

$$P(Y = y_i) = \frac{e^{-\mu_i} \mu^{y_i}}{y_i!} \qquad (1)$$

Where $P(Y = y_i)$ is the probability of nine month pregnant women entity i having antenatal care service visits in nine (9) months of pregnancy period and $\mu_i$is the Poisson parameter for pregnant woman i , which is equal to pregnant woman entity i's expected number of antenatal care service visits in nine (9) months, E(y_i). Poisson regression models are estimated by specifying the Poisson parameter μ_i (the expected number of antenatal care service visits) as a function of explanatory variables, the most common functional form being $\mu_i = \exp(x_i'\beta)$, Where x_i'=$(1, x_{i1}, x_{i2}, \ldots x_{ip})$is a vector of explanatory variables and β is a (p + 1)-dimensional column vector of unknown parameters to be estimated

$E(x) = var(y_i) = \mu_i$

The log-likelihood function is:

$$l(\mu_i) = l(\mu_i; y) = \sum_{i=1}^{n} \{y_i \ln(\mu_i) - \mu_i - \ln(y_i!)\}$$

Let X be a $n \times (p+1)$ matrix of explanatory variables. The relation ship between y_i and i^{th} row vector of X, x_i linked by $l(\mu_i)$ is: $\ln(\mu_i) = \eta_i = x_i{}^T\beta = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{i1} + \cdots + \beta_k x_{ik}$

The estimation is undertaken by using maximum likelihood method. There are two basic criteria commonly used to check the presence of over dispersion: the deviance, D(y,μ_i) or the pearson χ^2 statistic be greater than its degree of freedom. For the poisson regression, D(y, μ_i) and χ^2 are defined in expression below respectively.

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

$$\chi^2 = \sum_{i=1}^{n} \frac{(y_i - \widehat{\mu_i})^2}{\widehat{\mu_i}} \qquad (3)$$

However, these two rules of thumb can yield misleading inference from a direct likelihood point of view. Therefore, selecting between Poisson regression and an over dispersed Poisson model should be performed using some appropriate modeling procedure (Dejen et al., 2015; Dobson, 2002).

There are two principal assumptions in the Poisson model we need to regard: one is that events occur independently over time or exposure period, the other is that the conditional mean and variance are equal (Cameron, A. C. and P. K. Trivedi (1998)). The latter assumption is quite important. If it fails, the fitted model should be reconsidered.

Even though the Poisson model has served as a starting point for count or frequency analysis for several decades, researchers have often found that count data exhibit characteristics that make the application of the simple Poisson regression problematic. Specifically, Poisson models cannot handle over- and under-dispersion and they can be adversely affected by low sample means and can produce biased results in small samples. Therefore, it should be performed using some appropriate modeling procedure.

3.3.1.2Negative binomial regression model

The negative binomial model is an extension of the Poisson model to overcome possible over dispersion in the data (Lord, 2010). If a Poisson regression model doesn't fit the data and it appears that the variance of Y is increasing faster than the Poisson model allows (i.e. if a plot of the residuals versus linear predictors appears to fan out), then a simple scale-factor adjustment is not appropriate. One way to handle this situation is to fit a parametric model that is more dispersed than the Poisson. A natural choice is the negative binomial (John and Pamela, 2010). The probability mass function for the negative binomial distribution is:

$$f(y_i;\mu_i;\delta) = \frac{\Gamma\left(y_i + \frac{1}{\delta}\right)}{y_i!\,\Gamma\left(\frac{1}{\delta}\right)}(1+\delta\mu_i)^{\frac{-1}{\delta}}(1+\frac{1}{\delta\mu_i})^{-y_i}, \quad y_i \geq 0; \quad \delta > 0 \qquad (4)$$

With mean and variance are expressed as:

$E(y_i) = \mu_i = \exp(x_i'\beta)$, var $(y_i) = \mu_i(1+\ \delta\ )$

Where

- the term δ is the dispersion factor and it is constant
- we relate the parameters μ_i to covariates $x_i \epsilon R^p$ through the log-link functions; so that

$$log\mu_i = x_i{'}\beta \qquad (5)$$

Where x_i'=$\left(1, x_{i1}, x_{i2}, \ldots x_{ip}\right)$, $1 \times p$ row vector of covariates is the number of covariates in the model.

$\beta = (\beta 1, \beta 2, \ldots \beta p)'$ is the corresponding$(p+1) \times 1$ column vector of unknown regression parameters. The maximum likelihood estimation method is used to estimate the parameter vector

$$\xi = (\delta\ , \beta^T)^T$$

The likelihood function of the NB model based on a sample of n independent observations is given by

$$L(\mu;\ \delta\ ; y_i) = \prod_{i=1}^{n} \left\{ \frac{\Gamma\left(y_i + \frac{1}{\delta}\right)}{y_i!\,\Gamma\left(\frac{1}{\delta}\right)} (1 + \delta\ \mu i)^{\frac{-1}{\delta}} (1 + \frac{1}{\delta\ \mu i})^{-y_i} \right\} \tag{6}$$

Then the log-likelihood function is expressed as follows

$$l = logL(\mu;\ \delta\ ; y_i)$$

$$l = \sum_{i=1}^{n} \left\{ -\log(y_i!) + \sum_{k=1}^{y_i} \log(\delta y_i - \delta\, k + 1) - (y_i + 1/\delta)\log(1 + \delta\mu_i + y_i\log(\mu_i) \right\} \tag{7}$$

The likelihood equations for estimating μ_i and δ are obtained by taking the partial derivations of the log-likelihood function and setting them equal to zero. Thus, we obtain the first derivatives of

$l = logL(\mu;\ \delta\ ; y_i)$With respect to the underlying parameters as follows:

$$\frac{\partial\, l}{\partial\, \beta} = \frac{\partial\, l}{\partial\, \mu} \frac{\partial \mu}{\partial\, \beta} = \sum_{i=1}^{n} \left(\frac{y_{i-\mu_i}}{1+\delta\mu_i} \right) x_i\ ,$$

$$\frac{\partial\, l}{\partial\, \delta} = \sum_{i=1}^{n} \left\{ \left(\sum_{i=1}^{y_i} \frac{y_i - \mu_i}{\delta y_i - \delta k + 1}\right) + \frac{\log(1 + \delta\mu_i)}{\delta^2} - \frac{(y_i + \frac{1}{\delta})\mu_i}{1 + \delta\mu_i} \right\} \tag{8}$$

3.3.1.3Zero-inflated count regression models

There are situations where a major source of over-dispersion is a relatively large number of zero counts, and the resulting over-dispersion cannot be modeled accurately with negative binomial model. In such cases, one can use zero-inflated Poisson or zero-inflated negative binomial model to fit the data. Zero-inflated distributions can be formed from a component mixture of two distributions. They allow for zero-inflated data and involve a mixture of two distributions where the zeros are modeled separately from the counts. Let $f(y_i; \mu)$ be a distribution function count data, such as the Poisson and negative binomial distribution, with unknown parameters μ. Then, a zero-inflated distribution, denoted as ZI$f(y_i; \mu)$, is given by (Agarwal et al., 2002).

$$p(y_i|\omega, \mu) = \begin{cases} \omega(1 - \omega) f(y_i = 0; \mu), & y_i = 0 \\ (1 - \omega) f(Y_i = y_i; \mu), & y_i = 1,2 \ldots\ldots \end{cases} \tag{9}$$

The mean and variance of the ZI $f(y_i;\mu)$ distribution are given by

$E_{zi}f(y_i;\omega,\mu) = (1-\omega)E_f(y_i;\mu)$And

$var_{zi}\, f(y_i;\omega,\mu) = (1-\omega)\left[E_f{}^2(y_i;\mu)\right] - [(1-\omega)E_f(y_i;\mu)]^2$

$=(1-\omega)\left\{var_f(y_i;\mu)\right\}$.

3.3.1.4Zero-inflated Poisson (ZIP) regression model

ZIP model, well described by (Lambert, 1992) is a simple mixture model for count data with excess zeros. The model is a combination of a Poisson distribution and a degenerate distribution at zero. Specifically if $Y_i$is the number of ANC visits per pregnant mothers are dependent random variables having a zero-inflated Poisson distribution, the zeros are assumed to arise in two ways corresponding to distinct underlying states. The first state occurs with probability $\omega_i$and produces only zeros (mothers who are never attend for ANC), while the other state occurs with probability $1-\omega_i$and leads to a standard Poisson count with mean μ and hence a chance of further zeros (mothers who may not face pregnancy complication and born healthy child). In general, the zeros from the first state are called structural zeros and those from the Poisson distribution are called sampling zeros (Jansakul and Hinde, 2002). This two-state process gives a simple two-component mixture distribution with probability mass function

The Zero-inflated Poisson regression model is expressed as

$$p(Y_i = y_i = \begin{cases} \omega_i + (1-\omega_i)e^{-\mu},\ y_i = 0 \\ (1-\omega_i)\dfrac{e^{-\mu}\mu_i{}^{y_i}}{y_i!}, y_i = 1,2,..\ , 0 \le \omega_i \le 1 \end{cases} \tag{10}$$

The mean and variance of Zero-inflated (ZIP) distribution is given as

$$E_{ZIP}(y_i|\omega_i,\mu_i) = (1-\omega_i)\mu_i, \qquad and$$

$$var_{ZIP}(y_i|\omega_i,\mu_i) = E_{ZIP}(y_i|\omega_i,\mu_i)(1+\omega_i\mu_i)$$

To apply the ZIP model in practical modeling situations, (Agarwal et al., 2002; Afifi et al., 2007) suggested the following joint models for $\mu_i$andω_i

$$\log(\mu_i) = x_i{}^T\beta\ and \log\left(\frac{\omega_i}{1-\omega_i}\right) = z_i{}^T\Upsilon,\ i = 1,2,\dots,n \tag{11}$$

Where x_i and z_i are covariate matrices. β and Y are (p+1)x1 and (q+1)x1 vector of unknown parameters ,respectively. The vector of covariates x_i and z_i can be the same or different. For a random sample of observations $y_1, y_2, \ldots\ y_n$ the log-likelihood function $l(\mu; \omega; y)$ is given by

$$l = \sum_{i=1}^{n} \{\ln[\omega_i + (1-\omega_i)\mathrm{e}^{-\mu}] I_{(y_{i=0})}\} + [\ln(1-\omega_i) - \mu_i + y_i ln\mu_i - \ln(y_i\,!)] l_{(y_{i=0})} \quad (12)$$

Where I (.) is indicator function for the specified event, i.e. equal to 1 if the event is true and 0 otherwise. The first and the second derivatives of $l = l(\mu; \omega; y)$with respect to β and Y are as follows

$$\frac{\partial l}{\partial \beta_j} = \frac{\partial l(\mu,\omega)}{\partial \mu_i}\frac{\partial \mu_i}{\partial \beta_i} = \sum_{i=1}^{n}\left\{I_{(y_{i=0})}\left[\frac{-(1-\omega_i)\mu_i}{\omega_i + (1-\omega_i)\mathrm{e}^{-\mu_i}}\right] + I_{(y_i)}[y_i - \mu_i]\right\} x_{ij}, j = 1,2,\ldots,p$$

$$\frac{\partial l}{\partial \gamma_r} = \frac{\partial l(\mu,\omega)}{\partial \omega_i}\frac{\partial \omega_i}{\partial \gamma_i} = \sum_{i=1}^{n}\left\{I_{(y_{i=0})}\left[\frac{1-\mathrm{e}^{-\mu_i}}{\omega_i + ((1-\omega_i)\mathrm{e}^{-\mu_i})}\right] - I_{(y_{i>0})}[\frac{1}{1-\omega_i}]\right\} z_{ir},\ r = 1,2,\ldots q$$

3.3.1.5Zero-inflated negative binomial (ZINB) regression model

The zero-inflated negative binomial (ZINB) model is a general model for counts which nests the Zero-inflated Poisson (ZIP), negative binomial (NB), and Poisson models. A Zero-inflated negative binomial ZINB model for the response y_i can be written

$$p(Y_i = y_i) = \begin{cases} \omega_i + (1-\omega_i)(1+\delta\mu_i)^{-\frac{1}{\delta}} y_i = 0 \\ (1-\omega_i)\dfrac{\Gamma\left(y_i + \frac{1}{\delta}\right)}{y_i!\,\Gamma\left(\frac{1}{\delta}\right)}(1+\delta\mu_i)^{-\frac{1}{\delta}}\left(1 + \dfrac{1}{\delta\mu_i}\right)^{-y_i} \quad y_i < 0 \end{cases} \quad (13)$$

Where δ>0 is a dispersion parameter and is assumed not to depend on covariates. The mean and variance of the ZINB model are given by

$$E(Y_i) = (1-\omega_i)\mu_i \text{And}$$

$$\text{Var } (Y_i) = (1-\omega_i)(1+\omega_i\mu_i + \delta\mu_i)\mu_i$$

The parameters μ_i and $\omega_i$depend on vectors of covariates $x_i$and $z_i$respectively. The zero-inflated negative binomial (ZINB) distribution is not a standard generalized linear model (GLM) type, even when the over-dispersion parameter δ is known, and standard GLM fitting methods are not applied. To obtain the parameter estimates of ZINB regression models $\delta, \beta\ and\ \gamma$ the Newton-Raphson method or the method of Fisher scoring will be used. However, the method of Fisher scoring is more appropriate for ZINB regression because the second derivative $l = (\delta, \mu_i, \omega_i; y_i)$, is simplified by taking expectations (Agarwal et al., 2002; Agresti, 2003).

3.3.1.6The Poisson Hurdle Model

Poisson Logit Hurdle (PLH) model is a two-component model comprising of a hurdle component models zero versus non-zero counts, and a truncated Poisson count component is employed for the non-zero counts(Mullahy, 1986, Gurmu, 1998). Its probability density function is given as:

$$p(Y_i = y_i) = \begin{cases} \pi_0 & if\ y_i = 0 \\ (1-\pi_0)\dfrac{\exp(-\mu_i)\,{\mu_i}^{y_i}}{(1-\exp(-\mu_i)\,y_i!} & if\ y_i = 1,2,\dots. \quad 0 \le \pi_0 \le 1 \end{cases} \tag{14}$$

For PLH model, the most natural choice to model probability of zeros is to use a logistic regression model

$$logit(\pi_0) = \log\left(\frac{\pi_0}{1-\pi_0}\right) = {z_i}^T\gamma \tag{15}$$

Where $z_i = \left(1, z_{i1},\ z_{i2}, \dots, z_{iq}\right) is\ the\ i^{th}$ row of covariates matrix Z and $\gamma = \left(\gamma_1, \gamma_2, \dots \gamma_q\right)\ are$ unknown q-dimensional column vector of parameters. While the effect of covariates z_i on strictly positive (that is censored). Count data are modeled through Poisson regression:

$$\log(\mu_i) = {x_i}^T \tag{16}$$

$x_i = \left(1, x_{i1}, x_{i2}, \dots, x_{ip}\right) is\ the\ i^{th}\ row\ of\ covariate\ matrix\ x\ and\ \beta = (\ \beta_1,\ \beta_2, \dots\ \beta_p)$ are unknown p-dimensional column vector of parameters. This model was proposed originally by (Mullahy, 1986).

The log-likelihood function of a Logit-Poisson regression therefore, can be expressed as the sum of log-likelihood functions of two components as below:

$$l(\mu;\pi;y) = \sum_{i=1}^{n}\Big\{I_{(y_{i=0})}\log(\pi_0) + I_{y_i>0}[\log(1-\pi_0) - \mu_i + y_i\log(\mu_i) - \log\big(1 - Exp(\mu_i)\big) - \log(y_i!]\Big\} \tag{17}$$

3.3.1.7 The Negative Binomial Hurdle Model

Similarly, for the hurdle model, the Negative Binomial Hurdle can be used instead of Poisson distribution above in case of over-dispersion (Gurmu, 1998). We consider a hurdle negative binomial (HNB) regression model in which the response variable has the $y_i = (i = 1,2,3 \ldots n)$ has the distribution

$$p(Y_i = y_i) = \begin{cases} \pi_0 & \text{if } \; y_i = 0 \\ 1 - \pi_0 \dfrac{\Gamma(y_i + (1/\alpha)(1+\alpha\mu_i)^{-\frac{1}{\alpha}}(1+\frac{1}{\alpha\mu_i})^{-y_i}}{y_i!\,\Gamma(1/\alpha)(1-(1+\alpha\mu_i)^{-\frac{1}{\alpha}})}, & \text{if } \; y_i > 0 \end{cases} \quad 0 \le \pi_1 \le 1 \qquad (18)$$

Where $\alpha \geq 0$ is a dispersion parameter that is assumed not to depend on covariates. In addition, we suppose 0<π_0<1 and $\pi_0 = \pi_0(z_i)$ saisfy

The most natural choice to model probability of excess zeros is to use a logistic regression model:

$$\text{logit}(\pi_0) = \log\left(\frac{\pi_0}{1-\pi_0}\right) = \sum_{j=1}^{q} z_{ij}{}^{T}\gamma_j \qquad (19)$$

Where $z_i = (1, z_{i1}, z_{i2}, \ldots, z_{iq})$is the i^{th} row of covariates matrix Z and $\gamma = (\gamma_1, \gamma_2, \ldots \gamma_q)$ are unknown q-dimensional column vector of parameters. Impact of covariates on count data modeled through NB regression

$$\text{logit}(\mu_i) = \textstyle\sum_{j=1}^{p} x_{ij}\beta_j \qquad (20)$$

x_{ij} is is the covariates,β is is the coefficient of the independent variables in the regression model and p is the number of these independent variables.

We now obtain the log-likelihood function for the hurdle negative binomial regression model, we have

$$LL = \sum_{i=1}^{n}\left\{ I_{(y_{i=0})}\log(\pi_0) + I_{y_i>0}\begin{bmatrix} \log(1-\pi_0) - \dfrac{1}{\alpha}\log\big(1-(1+\alpha\mu_i)\big) - \log y_i! - y_i\log(1+\dfrac{1}{\alpha\mu_i} \\ -\dfrac{1}{\alpha}\log(\alpha\mu_i + 1) + \log\left[\dfrac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{\Gamma\left(\frac{1}{\alpha}\right)}\right] \end{bmatrix}\right\} \; (21)$$

3.3.2 **Multilevel Count Regression Models**

Multilevel modelling is an approach that can be used to handle *clustered* or *grouped* data. For simplicity of presentation, two-level models was used for this study, i.e., models accounting for number of ANC visits-level and regional -level effects. In this data structure, level-1 is the number of ANC visits and level-2 is the regional level. Within each level-2 unit there are n_j ANC visit in the j^{th} region.

3.3.2.1 **Multilevel Poisson regression model**

The multilevel Poisson model deals with certain kinds of dependence. The model can be further extended by including a varying exposure rate *m*. The multilevel Poisson regression model for a count Y_{ij} for i^{th} individual in the j^{th} group is expressed as follow (Joop, 2010)

$$Y_{ij}/\lambda_{ij}=\text{poisson}\ (m_{ij}, \lambda_{ij})$$

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

$$\log(\lambda_{ij}) = \eta_{ij} \tag{22}$$

Where, $\eta_{ij} = \beta_{0j} + \beta_{1j}x_{1ij} + \beta_{2j}x_{2ij} + \cdots + \beta_{kj}x_{kij}$ (23)

Letting $\beta_{0j}=\beta_0 + U_{0j}$ and

$$\beta_{hj} = \beta_h + U_{hij}$$

From equation (22) $\log(\lambda_{ij}) = \beta_0 + \sum_{h=1}^{k} \beta_h\, x_{hij} + U_{0j} + \sum_{h=1}^{k} U_{hj}x_{hij} \qquad h = 1,2, \dots, k$ (24)

The first part of equation (24) $\beta_0 + \sum_{h=1}^{k} \beta_h\, x_{hij} + U_{0j}$ is called the fixed part of the model. The second part $U_{0j} + \sum_{h=1}^{k} U_{hj}x_{hij}$ is the random part. The groups are characterized by k+1 random coefficients $U_{0j}, U_{1j}, \dots, U_{hj}$.The random coefficients are independent between groups, but may be correlated within groups. It is assumed that the vectors $(U_{0j}, U_{1j}, \dots, U_{hj})$ is distributed with means zero and has a multivariate normal distribution with a constant variance matrix. The variances and covariance's of the level two random effects are

$$var(U_{hj}) = \sigma_{hh} = {\sigma_h}^2, \qquad h = 0,1,2, \dots, k$$

$$cov(U_{hj}, U_{pj}) = \sigma_{hp}, \qquad p = 0,1,2, \dots, k\ for\ h \neq p$$

3.3.2.1.1 **Empty Model**

The empty two-level model for a count outcome variable refers to a population of groups (level two units) and specifies the probability distribution for group-dependent μ_{ij} in $Y_{ij} = \mu_{ij} + \varepsilon_{ij}$ without taking further explanatory variables into account. We focused on the model that specifies the transformed $\log(\mu_{ij})$ to have a normal distribution. This is expressed, for a general link function $\log(\mu)$, by the formula

$$\log(\mu_{ij}) = \beta_0 + U_{0j}$$

Where β_0 is a fixed coefficient and U_{0j} is a random term that is independently and normally distributed with mean 0 and variance ${\sigma_{u0}}^2$ (random intercept variance)(Sturman, 1999). This model is also named as empty Poisson regression model (null model). A null model contains only a response variable, and no explanatory variables other than an intercept. Thus, ${\sigma_{u0}}^2$ measures regional variations of number of antenatal care service visit attendances.

3.3.2.1.2 **The Random Intercept Model**

A random intercepts model is a model in which intercepts are allowed to vary, and therefore, the scores on the dependent variable for each individual observation are predicted by the intercept that varies across regions. That means the groups differ with respect to the average value of the response variable, but the relation between explanatory and response variables cannot differ between groups. The random intercept model expresses the natural log of μ_{ij} as a sum of a linear function of the explanatory variables. That is,

$$\log(\mu_{ij}) = \beta_{0j} + \beta_1 x_{1ij} + \beta_2 x_{2ij} + \cdots + \beta_k x_{kij}$$

$$= \beta_{0j} + \sum_{l=1}^{k} \beta_l x_{lij}$$

Where the intercept term β_{0j} is allowed to vary across the regions and is given by the sum of an average intercept β_0 and regions-dependent deviations U_{0j} ,that is

$$\beta_{0j} = \beta_0 + U_{0j}$$

As a result we have:

$$\log(\mu_{ij}) = \beta_0 + \sum_{l=1}^{k} \beta_l x_{lij} + U_{0j}$$

Note that in the above equation $\sum_{l=1}^{k} \beta_l x_{lij}$ is the fixed part of the model and the remaining U_{0j} is called the random part of the model. It is assumed that the random part of U_{0j}independent and normally distributed with mean zero and variance ${\sigma_{u0}}^2$

3.3.2.1.3 The Random Coefficients Model

A random slopes model is a model in which slopes are allowed to vary, and therefore, the slopes are different across regions. In other word, the relationship between an explanatory variable and the response is different across all regions. If we fit a model based on the same predictors on the response variable for all regions separately, we may obtain different intercept and slopes for each region. Now consider a model with group-specific regressions, on a single level one explanatory variable X

$$\log(\mu_{ij}) = \beta_{0j} + \beta_{1j} x_{1ij}$$

The intercepts β_{0j} as well as the regression coefficients or slopes, β_{1j} are group dependent. These group dependent coefficients can be split into an average coefficient and the group dependent deviation:

$$\beta_{0j} = \beta_0 + U_{0j}$$

$$\beta_{1j} = \beta_1 + U_{1j}$$

As the result:- $\log(\mu_{ij}) = (\beta_0 + U_{0j}) + (\beta_1 + U_{1j}) x_{1ij}$

$$= \beta_0 + \beta_1 x_{1ij} + U_{0j} + U_{1j} x_{1ij}$$

There are two random group effects, the random intercept U_{0j} and the random slope U_{1j} . It is assumed that the level two residuals U_{0j} and U_{1j} explanatory variable X. Thus, β_1 is the average regression coefficient like β_0 is the average intercept. The first part of equation $\beta_0 + \beta_1 x_{1ij} + U_{0j} + U_{1j} x_{1ij}$ $(\beta_0 + \beta_1 x_{1ij} + U_{0j})$ is called the fixed part of the model whereas the second part $U_{0j} + U_{1j} x_{1ij}$ is called the random part of the model.

The term $U_{0j} + U_{1j}x_{1ij}$ can be regarded as a random interaction between group and predictors(X). This model implies that the groups are characterized by two random effects: their intercept and their slope. These two group effects U_{0j} and U_{1j} will not be independent. Further, it is assumed that, for different groups, the pairs of random effects (U_{0j}, U_{1j}) are independent and identically distributed. Thus, the variances and covariance of the level-two random effects

$$var(U_{0j}) = \sigma_{00} = \sigma_0{}^2$$

$$var(U_{1j}) = \sigma_{11} = \sigma_1{}^2$$

$$cov(U_{0j}, U_{1j}) = \sigma_{01}$$

3.3.2.1.4 Testing the presence of correlation within the regions (Intra-class Correlation)

Intra-class correlation coefficient (ICC), ρ, was calculated for each model to test the presence of intra-class correlation. The intra-class correlation coefficient (ICC) measures this degree of correlation. The ICC is the proportion of variance in the outcome variable that is explained by the grouping structure of the hierarchical model. It is calculated as a ratio of group-level error variance over the total error variance:

$$\rho = \frac{\sigma_{u_0}^2}{\sigma_{u_0}^2 + \sigma_e^2} \qquad (25)$$

Where $\sigma_{u_0}^2$ is the variance of the level-2 residuals and σ_e^2 is the variance of the level-1 residuals. In other words, the ICC reports on the amount of variation *unexplained* by any predictors in the model that can be attributed to the grouping variable, as compared to the overall unexplained variance (within and between variance)

If all the observations are independent of one another, the ICC equals 0. At the other extreme, if all the responses from observations in all clusters are exactly the same, the ICC equals 1. A nonzero ICC implies that the observations are not independent. If observations are highly correlated, the variance of observations at Level 1, σ_e^2, becomes smaller(Hox, 2002).

The ICC is interpreted in four ways. First, the ICC represents the degree of common environments that observations share. The ICC would increase if observations in the same cluster were under more similar environments and, as a result, if the responses of observations became more alike. The second interpretation of the ICC is the proportion of total variance (i.e., cluster plus individual variance) that is attributed to the cluster level. Therefore, as the relative variance of the clusters increases, the less likely you are to assume that the groups are similar. The third interpretation of the ICC is the degree of homogeneity of Level 1 within Level 2 (i.e., the quantity of similarity among observations at the cluster level). If observations were not correlated, they would not affect one another nor would they be similar at all (i.e., no homogeneity). The last interpretation of the ICC is the anticipated correlation between two observations that are randomly chosen from the same cluster (e.g., correlation of two nurses within the same hospital) (Hox, 2002) Kreft& De Leeuw, 1998).

3.3.2.2**Multilevel negative binomial regression model**

Count data with over-desperation relative to a Poisson distribution are common in many biomedical applications. A popular approach to the analysis of such data is to use NB regression model. Often, because of the hierarchical study design or the data collection procedure, over desperation and lack of independence may occur simultaneously, which render the standard NB model in adequate. To account for the over-desperation and the inherent correlation of observations, a class of multilevel NB regression model with random effects is presented. The multilevel NB model is then generalized to cope with a more complex correlation structure. The multilevel NB model derives by allowing for between regional random variations of the expected number of ANC visits μ_{ij}.

$$ln\mu_i = \eta_{ij} + e_{ij}$$

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

$$p(Y_{ij} = y_{ij}) = \frac{\exp(-\exp(\eta_{ij} + e_{ij}))\exp(\eta_{ij} + e_{ij})^{y_{ij}}}{y_{ij}!}$$

The resulting multilevel negative binomial regression model is given by;

$$P\left(Y_{ij} = y_{ij}\right) = \frac{\Gamma(y_{ij} + v)}{y_{ij}!\,\Gamma(v)} \frac{V^{v} {\mu_{ij}}^{*y_{ij}}}{(v + {\mu_{ij}}^{*})^{v+y_{ij}}} y_{ij} = 0,1,2,\ldots, \tag{26}$$

With mean and variance given respectively:

$$E\left(Y_{ij}\right) = {\lambda_{ij}}^{*} = \log(\eta_{ij})$$

$$var\left(Y_{ij}\right) = {\lambda_{ij}}^{*} + a({\lambda_{ij}}^{*})^{2}$$

Where,$\eta_{ij} = \beta_{0j} + \beta_{1j}x_{1ij} + \beta_{2j}x_{2ij} + \cdots + \beta_{kj}x_{kij}$

3.3.2.3**Multilevel zero-inflated Poisson regression model**

Count data with excess zeros relative to a Poisson distribution are common in many biomedical applications. A popular approach to the analysis of such data is to use a zero-inflated Poisson (ZIP) regression model. Often, because of the hierarchical study design or the data collection procedure, zero-inflation and lack of independence may occur simultaneously, which render the standard ZIP model in adequate. To account for the preponderance of zero counts and the inherent correlation of observations, a class of multilevel ZIP regression model with random effects is presented. The multilevel ZIP model is then generalized to cope with a more complex correlation structure (Andy et al., 2006). Suppose a discrete count response variable Y follows a ZIP distribution:

$$P\left(Y_{i} = y_{ij}\right) = \begin{cases} \phi + (1-\phi)\mathrm{e}^{-\mu_{i}}, & y_{i} = 0 \\ (1-\phi)\dfrac{\mathrm{e}^{-\mu_{i}}\mu_{i}}{y_{i}!}, & y_{i} = 1,2,\ldots \end{cases} \tag{27}$$

Where , $0 \leq \phi_{i} \leq 1$ so that, it is incorporates more zeros than those permitted under the poisson assumption ($\phi = 0$), where as $\phi < 0$ corresponds to the-deflated situation. The ZIP distribution may be regarded as a mixture of a Poisson (λ) and a degenerate component placing all its mass at zero. Recently, the ZIP regression model has been extended to the random effects setting, whereby random components $s_{i}$and $v_{i}$are incorporated within the logistic and Poisson linear predictors to account for the dependence of observations within clusters. These random effects ZIP models are mother-specific in the sense that the random effects $s_{i}$and v_{i} so introduced are specific to the i^{th} region. In the following, a multilevel ZIP regression model is developed to handle correlated count data with extra zeros.

Without loss of generality, consider the two-level hierarchical situation where Y_{ij}represents the j^{th}observation of number of ANC visits in the i^{th}individual region (i = 1,2, … , m and j = 1,2, … , n_i). Let m be the total number of individuals in each region and$N = \sum_{i=1}^{m} \sum_{j=1}^{n_i} ni$ gives the total number of observations. The observations may be taken to be independent between regions, but certain within-region and within-individual correlations are anticipated, which can be modeled explicitly through random effects attached to the linear predictors:

$$\log(\lambda_{ij}) = \beta_0 + \sum_{h=1}^{k} \beta_h x_{hij} + U_{0j} + \sum_{h=1}^{k} U_{hj} x_{hij}$$

$$x_{ij}'\beta + x_{ij}'U$$

$$\log\left[\frac{\phi}{(1-\phi_{ij})}\right] = \xi = z_{ij}{}^{T}\gamma + v_{0j} + \sum_{h=1}^{k} U_{hj} Z_{hij} \qquad (28)$$

Here, the covariates x_{ij} and z_{ij}appearing in the respective Poisson and logistic components are not necessarily the same, and β and γ are the corresponding vectors of regression coefficients (Moghimbeigi et al., 2008; Meng, 1997). The EM algorithm was also used for over-dispersed count data (McLachlan and Krishnan, 2008).

3.3.2.4**Multilevel ZINB Regression Model**

Multilevel ZINB regression model is proposed for over-dispersed count data with extra zeros. A multilevel ZINB regression incorporating random effects to account for data dependency and over-dispersion is used(Moghimbeigi et al., 2008). Let $Y_{ij} (i = 1,2, \dots n; j = 1,2, \dots m)$ be a count and the number of ANC service visits of the i^{th} woman in j^{th} region follows a ZINB distribution:

$$p(Y_{ij} = y_{ij}) = \begin{cases} \pi_{ij} + \dfrac{(1-\pi_{ij})}{(1+\alpha\mu_{ij})^{-\frac{1}{\alpha}}}, & if \;\; y_{ij} = 0 \\ 1 - \pi_{ij} \dfrac{\Gamma\left(y_{ij} + \frac{1}{\alpha}\right)}{y_{ij}!\,\Gamma\left(\frac{1}{\alpha}\right)} (1+\alpha\mu_{ij})^{-\frac{1}{\alpha}} \left[1 + \dfrac{1}{\alpha\mu_{ij}}\right]^{-y_{ij}}, & if \;\; y_{ij} > 0 \end{cases} \qquad 0 \le \pi_{ij} \le 1$$

In this study, mothers are nested in region and number of antenatal care service visits is taken to be the response variable. Let n be the total number of women in each region and $\sum_{j=1}^{m} \sum_{i=1}^{ni} ni$ gives the total number of observations. Hence the responses of number of antenatal care service visits which belong to different region are independent, while they are correlated for those who live in the same region. This dependence can be modeled explicitly by considering suitable random effects in the linear predictor. Negative binomial models for counts permit μ to depend on explanatory variables. Then the two level ZINB regression model can be expressed in vector form as:

$$\log(\mu_{ij}) = \beta_0 + \sum_{l=1}^{k} \beta_1 x_{lij} + U_{0j} + \sum_{l=1}^{k} U_{ij} x_{lij}$$

$$\log(\pi_{ij}) = \log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \gamma_0 + \sum_{l=1}^{k} \gamma_1 Z_{lij} + W_{0j} + \sum_{i=1}^{k} W_{lj} Z_{lij}$$

Where, the covariates x_{lij} *and* Z_{lij} appearing in the respective negative binomial and logistic components are not necessarily the same, β *and* γ are the corresponding vectors of regression coefficients (Moghimbeigi et al., 2008, Meng and Van Dyk, 1997). The vectors W_j *and* U_j denote the region-specific random effects for simplicity of presentation. The random effect W *and* u assumed to be independent and normally distributed with mean zero and variance ${\sigma_W}^2$ *and* ${\sigma_U}^2$ respectively.

3.3.2.5**Multilevel Hurdle Regression Model**

The hurdle model (Mullahy, 1986) has mostly been adopted to conduct an economic analysis of health care utilization. Count data with excess zeros relative to a Poisson distribution are common in many economical applications. A popular approach to the analysis of such data is to use a Hurdle Poisson regression model. Often, because of the hierarchical study design or the data collection procedure, zero-inflation and lack of independence may occur simultaneously, which the standard Hurdle Poisson regression model inadequate. To account for the preponderance of zero counts and the inherent correlation of observations, a class of multilevel Hurdle Poisson regression model with random effects is presented. In this study, suppose that Y_{ij} is the number of ANC follow-ups in i^{ith} woman and in the region. Thus, multilevel Poisson Hurdle model can be written as follows

$$p(Y_{ij} = y_{ij}) = \begin{cases} \pi_{ij} & if\ \ y_{ij} = 0 \\ (1-\pi_{ij})\dfrac{\exp(-\mu_{ij})\,{\mu_{ij}}^{y_{ij}}}{(1-\exp(-\mu_{ij})y_{ij}!}\ , & if\ \ y_{ij} = 1,2,\ldots \end{cases} \quad 0 \le \pi_{ij} \le 1$$

In the regression setting, both the mean μ_{ij} and zero proportion π_{ij} parameters are related to the covariate vectors X_{ij} and Z_{ij} respectively. Moreover, responses within the same region are likely to be correlated. To accommodate the inherent correlation, random effects U_j and W_j are incorporated in the linear predictors η_{ij} for the Poisson part and ξ_{ij} for the zero part. The Hurdle Poisson mixed regression model is:-

$$\eta_{ij} = \log(\mu_{ij}) = x_{ij}{}^{T}\,\beta + U_j$$

$$\xi_{ij} = \log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = Z_{ij}{}^{T} + W_j$$

Where, β and γ are the corresponding $(p+1)\times 1$ and $(q+1)\times 1$ vector of regression coefficients. The random effects U_j and W_j are assumed to be independent and normally distributed with mean 0 and variance $\sigma_U{}^2$ and $\sigma_W{}^2$ respectively (Harvey, 2003)

3.3.3 **Parameter Estimation**

The most commonly used methods of estimating the parameter of a count regression model is the method of maximum likelihood estimation (MLE). The method maximum likelihood parameter estimation is to determine the parameters that maximize the probability (likelihood) of the sample data. MLE methods are versatile and apply to most models and to different types of data. The principle of MLE, originally developed by R.A. Fisher in the 1920s, states that the desired probability distribution is the one that makes the observed data ‘‘most likely,’’ which means that one must seek the value of the parameter vector that maximizes the likelihood function.

In general, the generalized linear models don’t have closed form of maximum likelihood function, to approximate MLEs of GLM we rely on Newton-Raphson algorithm. The log likelihood functions of β

$$l(\beta,\phi) = \sum\left\{\frac{(y_i\theta_i - b(\theta_i))}{\phi} + c(y_i,\phi)\right\}$$

$$=\sum l_i\,(\theta_i,\phi) = \sum l_i$$

Where,θ_i=$(x_i{}'\beta) = \theta(\eta_i)$

The MLE of β are obtained by maximizing the log-likelihood functions$l(\beta, \theta)$. Where θ known and monotone function; then the likelihood function of GLM is depends on β only through linear predictor η

The MLE of β are the solutions of the simultaneous equations of

$$\frac{\partial l(\beta, \phi)}{\partial \beta} = \sum \frac{\partial l_i}{\partial \beta_i} = 0$$

3.3.4 **Assessing Model Adequacy**

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

3.3.4.1**Wald Test**

The Wald test statistic is commonly used to test the significance of individual regression coefficients for each independent variable. Suppose we are testing $H_0: \beta = \beta_0$ then with non-null standard error of $\hat{\beta}$, the test statistic is

$$\boldsymbol{Z} = \frac{\widehat{\boldsymbol{\beta}} - \beta_0}{\boldsymbol{SE}(\widehat{\boldsymbol{\beta}})} \tag{29}$$

Has an approximate standard normal distribution. The multivariable extension for the Wald test of

$H_0: \beta = \beta_0$ has test statistic

$$w = (\hat{\beta} - \beta_0)^T [cov(\hat{\beta})]^{-1} (\hat{\beta} - \beta_0) \tag{30}$$

Where $cov(\hat{\beta})$ denote the asymptotic covariate matrix of $\hat{\beta}$ and is the inverse of the information matrix. The (j,k) element of the information matrix is

$$-E(\frac{\partial^2 l(\beta)}{\partial \beta_j \partial \beta_k})$$

The asymptotic multivariable normal distribution for $\hat{\beta}$ implies an asymptotic distribution for W. The degrees of freedom equal the rank of $cov(\hat{\beta})$, which is the number of non-redundant parameters in β (Joop, 2010).

3.3.4.2 **Likelihood Ratio Test (LRT)**

The negative binomial (NB) regression model reduces to the Poisson regression model as $\alpha \rightarrow 0$. The test for over-dispersion in NB regression model, $H_0: \alpha = 0 \; vs \; H_1: \alpha > 0$, can be performed using likelihood ratio test (LRT), $LRT = 2(lnL_1 - \ln L_0)$, where L_1 and L_0 are the models' log likelihood under alternative and null hypothesis. Since the null hypothesis is on the boundary of parameter space, the LRT is asymptotically distributed as half of probability mass at zero and half of chi-square with one degree of freedom (Lawless, 1987). In other words, to test the null hypothesis at significance level α, the critical value of chi-square distribution with significance level 2α is used, or reject H_0 if $T > {\chi^2}_{1-2\alpha(1)}$.

3.3.4.3 **Vuong's Test**

For non-nested models, a comparison between models with p.m.f. $p_1(.)$ and $p_2(.)$ can be performed using Vuong test, (Vuong, 1989; Greene, 2007).

$$v = \frac{\bar{m}\sqrt{n}}{sd(m)} \tag{31}$$

Where *m* is the mean of m_i, $sd(m)$ is the standard deviation of m_i, *n* is the sample size and

$$m_i = \ln\left(\frac{p_{1i(y_i)}}{p_{2i(y_i)}}\right)$$

The Vuong test statistic follows a standard normal distribution. As an example, for 0.05 significance level, the first model is "closer" to the actual model if *V* is larger than 1.96. In the other hand, the second model is "closer" to the actual model if *V* is smaller than -1.96, otherwise, neither model is "closer" to the actual model and there is no difference between using the first or the second model. For models with unequal number of parameters, the equation for m_i in Vuong test is slightly modified to account for the difference in the number of parameters,

$$m_i = \ln\left[\frac{p_{1i(y_i)}}{p_{2i(y_i)}}\right] - \frac{k_1 - k_2}{2}\ln(n)$$

Where k_1 and k_2 are the number of parameters model 1 and 2 respectively.

3.3.5 **Goodness of-fit tests**

In this section, several goodness-of-fit measures was briefly discussed, including the Pearson chi-squares, deviance, likelihood ratio test, Akaike Information Criteria (AIC) and Bayesian information criteria (BIC). Since these measures are used in the Generalized Linear Model with Poisson error structure for claim count or frequency analysis, the same measures may also be implemented to regression models of Negative binomial and Generalized Poisson as well.

3.3.5.1**Pearson chi-square**

A standard measure of goodness of fit for any model of yi with mean λ*i* is the Pearson statistic:

$$\chi^2 = \sum_{i}^{n} \frac{(y_i - \lambda_i)^2}{var(y_i)}$$

For an adequate model, the statistic has an asymptotic chi-squares distribution with n – k degrees of freedom, where n denotes the number of observations and k the number of unknown regression parameters in the model.

3.3.5.2**Deviance Statistic**

The maximum possible value of the likelihood for a given data set occurs if the model fits the data exactly. This occurs if observed counts are close with predicted. The difference between the log-likelihood functions for two models is a measure of how much one model improves the fit over the other. A special case of this was defined as the deviance. Let $l(y)$ denote the loglikelihood for the saturated model (which has as many coefficients as observations in the data set), and $l(\hat{\lambda})$ denote log-likelihood of current model (the fitted model) for all the observations in the sample. Then the deviance is defined as:

$$D = 2\{l(y) - l(\hat{\lambda})\}$$

Which is twice the difference between the maximum log-likelihood achievable and the loglikelihood of the fitted model. For an adequate model, D also has an asymptotic chi-squares distribution with n – k degrees of freedom. Therefore, if the values for both Pearson chisquares and D are close to the degrees of freedom, the model may be considered as adequate. The deviance could also be used to compare between two nested models, one of which is a simplified version of the other. Let D_1 and df_1 be the deviance and degrees of freedom for such model, and D_2 and df_2 be the same values by fitting a simplified version of the model. The chi-squares statistic is equal to $(D_2 - D_1)/ (df_2 - df_1)$ and it should be compared to a chi-squares distribution with $(df_2 - df_1)$ degrees of freedom.

3.3.5.3 **Likelihood ratio**

The advantage of using the maximum likelihood method is that the likelihood ratio test may be employed to assess the adequacy of the negative binomial over the Poisson because negative binomial will reduce to the Poisson when the dispersion parameter, α, equals zero. In this study a likelihood ratio was used to compare the Poisson with the negative binomial and zero-inflated Poisson with zero-inflated negative binomial since Poisson is nested on negative binomial and zero-inflated Poisson is nested in zero-inflated negative binomial.

However this will not be used to compare Poisson or negative binomial with the zero inflated Poisson and negative binomial as long as these models are not nested one on the other.

The likelihood ratio statistic is given by:

$$T = 2\{l_1 - l_0\}$$

Where, $l_1$and l_0 are the model's log likelihood under the alternative and null hypothesis, respectively. T has a chi-square distribution with one degrees of freedom. This method is not appropriate for models which are not nested. In such situations, we will use another method such as the Akakie information criteria (AIC) and Bayesian information criteria (BIC).

3.3.5.4 **Information Criteria (AIC and BIC)**

When several models are available, one can compare the models' performance based on several likelihood measures which have been proposed in statistical literatures. Two of the most regularly used measures are Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). The AIC penalizes a model with larger number of parameters, and is defined as $= -2lnL + 2P$, where $2lnL$ denotes the fitted log likelihood and *p* the number of parameters. The BIC penalizes a model with larger number of parameters and larger sample size, and is defined as $BIC = -2lnL + pln(n)$, where $2lnL$ denotes the fitted log likelihood, *p* the number of parameters and *n* the sample size (Ismail N., Z. H, 2013).

3.3.6 **Statistical software packages**

In this study, the researcher used R vision 3.6.1 statistical software packages for overall analysis of the data and SPSS version 20 was used for data entry.

Chapter Four

4 Results and Discussions

4.1 Descriptive Statistics

In this study, 7174 women were considered to determine factors that affect number of ANC service visits. Table 4.1 shows the descriptive results of number of antenatal care visits per mother. It indicated that more than 34% of mothers did not take any antenatal care, which indicates excess zero and less percentage of non-zero counts. And also the variance of dependent variable is greater than the mean, implying there is possibility of over dispersion.

Table 4.1 Frequency distribution of Number of antenatal care visits per women

ANC per Women	number of mothers that are experienced to ANC	Percent
0	2481	34.6
1	342	4.8
2	563	7.8
3	1187	16.5
4	1136	15.8
5	621	8.7
6	402	5.6
7	187	2.6
8+	255	3.6
Total	**7174**	**100**
Mean	**2.57**	
Variance	**5.512**	

Table 4.2 presents summary statistics of the variables that are assumed to affect antenatal care visits. The variables included are region, place of residence, mothers' education level, husband/partner's education level, mother's age, wealth index, pregnancy complication, Distance from health facility, peer influence, frequency of watching television, supportive partner and wantedness of pregnancy. The total number of women considered in this study was 7174 of which 4693(65.4%) of them experienced one or more antenatal care visit follow ups and the rest 2481(34.6%) did not experienced to any ANC service visits. Of the total women, only 255 (3.6%)

took 8 or more (which is recommended by WHO) ANC service follow up. 108(1.51%) and 520(7.25%) did not attended to ANC service in age groups of 15-19 and 30-34 respectively.

Another maternal variable that possibly has a strong bearing on ANC follow up is type of place of residence. Regarding to type of place of residence, 117(1.63%) and 2364(32.95%) were not attended for ANC in urban and rural areas. Of 255 women who took ANC service eight times or more, 196(2.73%) were from urban and the rest 59(0.82%) were from rural. Overall, more than three fourth 5667 (78.99%) of the respondents (mothers) live in rural areas, while less than one-fourth 1507 (21.01%) of them live in urban areas.

From a theoretical perspective, place of residence is an important determinant of antenatal care service. Mothers living in urban areas have a higher chance of getting health service and are aware of the benefit of medication than mothers who reside in rural areas. According to various literatures, maternal education level strongly affects ANC follow up. Table 4.2 reveals that there is an increasing trend in antenatal care service visits with regards to education level of mothers (that is, the probability of attending for ANC service increase as education level increases). In particular, the percentage of mothers who did not attended for ANC follow up was 28.14% for those with no education, 5.56% for those with primary education and 0.88% for those with secondary and higher education.

Husbands'/parents' education level shows the same result as mothers' education, that is, women living with illiterate Husbands/parents had low chance of visiting the service. In particular, the percentage of mothers who did not attended for ANC follow up was 23.07% for those with illiterate husbands/parents, 8.85% for those with primary education and 2.66% for those with secondary and higher education. On the other sides, women living with educated Husbands/parents has high chance of enjoying the antenatal care service. That is, of 255 women who visited the recommended number of antenatal care service, 0.4% of their husbands/parents were illiterate, 0.75% were primary and 2.4% of them were secondary and higher education level.

Concerning region, women living in Oromia and Somali had the highest proportion of not attending ANC service visits i.e. of 2481 women who did not visited the service, 503(7.01%) and 455(6.34%) respectively from Oromia and Somali regions while Addis Ababa city administration had the lowest proportion of not attending ANC service visits (only 12(0.17%)) and also among the 255 women who attended eight or more antenatal care service visits(the recommended number of ANC service visits),115(1.6%) were from Addis Ababa city administration. As far as the Wealth Index is concerned, the financial problem decreases the probability to attend desired number of ANC service follow up. Particularly, among 2481 women who did not taken antenatal care service, 1332 (18.57%) of them were poorest. On the other hand, of 255 women who had visited ANC follow up eight times or more, 101(1.41%) were richest. Generally, the richest women are most probable to visit the service and the reverse is true for the poorest women.

Moreover, the rest predictor variables that were not discussed above are listed below the table with regard to their percentage corresponding to the response variable.

Table 4.2 Summary statistics of predictor variables over the number of antenatal care visits in Ethiopia (in percent).

Independent variables	**Categories of Variables**	**Number of Antenatal care visits**									
		0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8+**	**Total**
Age groups	**15-19**	1.51	0.29	0.43	1.05	0.91	0.35	0.26	0.07	0.13	**4.99**
	20-24	6.48	1.17	1.78	3.71	3.51	2.02	0.93	0.47	0.68	**20.77**
	25-29	8.70	1.24	2.15	4.86	4.67	2.48	1.83	1.00	1.06	**27.99**
	30-34	7.25	1.10	1.69	3.23	3.36	1.74	1.41	0.63	0.88	**21.29**
	35-39	6.31	0.66	1.16	2.41	2.24	1.45	0.81	0.28	0.60	**15.92**
	40-44	3.19	0.21	0.47	0.89	0.91	0.46	0.26	0.13	0.20	**6.72**
	45-49	1.14	0.10	0.17	0.39	0.24	0.15	0.10	0.03	0.01	**2.33**
	Total	**34.58**	**4.77**	**7.85**	**16.55**	**15.83**	**8.66**	**5.60**	**2.61**	**3.55**	**100**
Regions	**Tigray**	1.10	0.60	0.98	1.98	2.97	1.81	0.77	0.18	0.28	**10.66**
	Afar	5.02	0.63	0.81	1.06	0.63	0.40	0.15	0.14	0.15	**8.99**
	Amhara	3.60	0.53	0.88	2.41	1.48	0.85	0.40	0.29	0.20	**10.64**
	Oromia	7.01	0.61	1.03	2.47	1.70	0.88	0.46	0.08	0.11	**14.36**
	Somali	6.34	0.85	1.06	1.53	0.67	0.36	0.25	0.03	0.10	**11.19**
	Benishangul	2.59	0.25	0.50	1.46	2.16	0.79	0.15	0.07	0.04	**8.03**
	SNNPR	3.72	0.39	1.12	2.30	2.72	1.14	0.56	0.29	0.18	**12.42**
	Gambela	3.00	0.17	0.47	1.21	1.25	0.66	0.52	0.10	0.06	**7.43**
	Harari	1.30	0.54	0.71	1.12	0.68	0.28	0.33	0.38	0.38	**5.72**
	Addis Adaba	0.17	0.07	0.07	0.25	0.81	0.79	1.05	0.42	1.60	**5.23**
	Dire Dawa	0.74	0.13	0.22	0.75	0.77	0.68	0.96	0.63	0.46	**5.34**
	Total	**34.58**	**4.77**	**7.85**	**16.55**	**15.83**	**8.66**	**5.60**	**2.61**	**3.55**	**100.00**

Place of residence	**Urban**	1.63	0.85	1.10	3.32	4.40	2.87	2.75	1.35	2.73	**21.01**
	Rural	32.95	3.92	6.75	13.23	11.43	5.78	2.86	1.25	0.82	**78.99**
	Total	**34.58**	**4.77**	**7.85**	**16.55**	**15.83**	**8.66**	**5.60**	**2.61**	**3.55**	**100.00**
Educational level of Mother											
	No education	28.14	3.33	5.23	8.95	7.32	3.71	2.19	1.03	0.70	**60.59**
	Primary	5.56	1.07	2.09	5.76	5.62	2.96	2.05	0.81	1.09	**27.00**
	Secondary	0.78	0.18	0.45	1.23	2.01	1.21	0.86	0.42	0.88	**8.02**
	Higher	0.10	0.18	0.08	0.61	0.89	0.78	0.50	0.35	0.89	4.39
	Total	**34.58**	**4.77**	**7.85**	**16.55**	**15.83**	**8.66**	**5.60**	**2.61**	**3.55**	**100.00**
Frequency of watching TV											
	Not at all	32.00	4.00	6.55	12.55	11.11	5.38	2.91	1.23	0.86	**76.60**
	Less than once a week	1.78	0.33	0.70	1.87	1.45	1.06	0.68	0.40	0.43	**8.71**
	At least once a week	0.79	0.43	0.60	2.13	3.28	2.22	2.01	0.98	2.26	**14.69**
	Total	**34.58**	**4.77**	**7.85**	**16.55**	**15.83**	**8.66**	**5.60**	**2.61**	**3.55**	**100.00**
Wealth Index	**Poorest**	18.57	2.20	2.91	4.45	3.12	1.45	1.06	0.42	0.24	**34.42**
	Poorer	5.72	0.88	1.58	3.57	3.47	1.83	0.91	0.38	0.43	**18.75**
	Middle	4.34	0.60	1.38	3.42	3.42	1.48	1.25	0.60	0.60	**17.08**
	Richer	3.53	0.46	1.25	2.65	2.93	1.77	1.12	0.57	0.88	**15.15**
	Richest	2.44	0.63	0.72	2.47	2.90	2.13	1.27	0.64	1.41	**14.61**
	Total	**34.58**	**4.77**	**7.85**	**16.55**	**15.83**	**8.66**	**5.60**	**2.61**	**3.55**	**100.00**
Pregnancy complication	**No**	29.13	3.60	5.63	9.67	7.61	4.13	2.44	0.99	1.06	**64.26**
	Yes	5.45	1.17	2.22	6.87	8.22	4.53	3.16	1.62	2.50	**35.74**
	Total	**34.58**	**4.77**	**7.85**	**16.55**	**15.83**	**8.66**	**5.60**	**2.61**	**3.55**	**100.00**
Husband Educational level											
	No education	23.07	2.54	3.97	6.33	5.02	2.52	1.63	0.64	0.40	**46.12**
	Primary	8.85	1.66	2.75	6.26	5.85	2.98	1.71	0.91	0.75	**31.73**
	Secondary	1.67	0.38	0.77	2.40	3.01	1.45	1.14	0.53	1.05	**12.39**
	Higher	0.99	0.20	0.36	1.56	1.95	1.70	1.12	0.53	1.35	**9.76**
	Total	**34.58**	**4.77**	**7.85**	**16.55**	**15.83**	**8.66**	**5.60**	**2.61**	**3.55**	**100.00**
Distance to health facility											
	No problem	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.01**

	Big problem	23.84	2.62	3.89	7.96	6.86	3.82	2.08	1.02	0.74	**52.82**
	Not a big problem	10.75	2.13	3.96	8.59	8.98	4.84	3.53	1.59	2.82	**47.17**
	Total	**34.58**	**4.77**	**7.85**	**16.55**	**15.83**	**8.66**	**5.60**	**2.61**	**3.55**	**100.00**
Peer influence :	**No problem**	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.01**
	Big problem	14.01	1.59	2.16	4.68	3.96	2.23	1.24	0.54	0.53	**30.95**
	Not a big problem	20.57	3.16	5.69	11.86	11.88	6.43	4.36	2.06	3.02	**69.04**
	Total	**34.58**	**4.77**	**7.85**	**16.55**	**15.83**	**8.66**	**5.60**	**2.61**	**3.55**	**100.00**
	Supportive parents										
	No problem	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.01**
	Big problem	17.84	2.04	2.89	6.29	5.13	2.70	1.46	0.74	0.75	**39.84**
	Not a big problem	16.74	2.72	4.96	10.26	10.71	5.95	4.14	1.87	2.80	**60.15**
	Total	**34.58**	**4.77**	**7.85**	**16.55**	**15.83**	**8.66**	**5.60**	**2.61**	**3.55**	**100.00**
Wantedness of pregnancy											
	Then	27.82	3.89	6.34	13.30	12.16	7.00	4.40	2.16	2.73	**79.80**
	Later	4.36	0.59	1.10	2.20	2.51	1.18	0.88	0.33	0.63	**13.79**
	No more	2.40	0.29	0.40	1.05	1.17	0.47	0.32	0.11	0.20	**6.41**
	Total	**34.58**	**4.77**	**7.85**	**16.55**	**15.83**	**8.66**	**5.60**	**2.61**	**3.55**	**100.00**

4.2 Single-level Analysis

4.2.1 Variable Selection method

For the identification of determinant predictors of number of antenatal care visits at the first glance uni-variable analysis was performed using Poisson regression model and all the explanatory variables included in the model are chosen in advance with backward selection method was used to select variables before applying different count models. The result recognized that: age, type of place of residence, wealth index, Mother educational level, husband educational level, frequency of watching television, distance from health facility, wantedness of pregnancy and pregnancy complication were are statistically significant and the other variables are found to be non-significant and thus excluded from analysis. After Poisson regression model, the analysis using other count regression models (NB, ZIP, ZINB, HP and HNB) are used with variables selected using backward variable selection method under Poisson and NB.

The basic difference between the single level and multilevel model here is that the single level only tells whether there is a difference in number of ANC service visits between regions, while multilevel modeling reveals the magnitude of variation of number of ANC service visits from individual mothers and its significance between regions. Thus, investigating the existence and magnitude of number of ANC service visits variation among regions are our main subsequent task.

The analysis concerns a multilevel modeling of number of ANC service visits determinants from individual mothers nested within 11 regions of Ethiopia under count regression models. The results presented in the subsequent section are obtained using R packages of the latest version 3.6.1.

4.3 Multilevel Count Analysis of the Data

In the multilevel analysis, a two -level structure was used with regions as the second-level units and individual mother as the first level units. In this study we considered multilevel models to allow for and to explore between-regional variation of number of antenatal care service visits. The data have a two -level hierarchical structure with 7174 mothers at level 1, nested within 11 regions at level 2.

4.3.1 Model selection and heterogeneity test

4.3.1.1 Test of Heterogeneity

A likelihood ratio test is applied to assess heterogeneity of the number of antenatal care service visit per mother among the 11 groups (9 regions and 2 city administrations). Comparisons of multilevel (Poisson, NB, ZIP, ZINB, HP and HNB) models with their single level count model, with LRT statistic given in Table 4.3. The values of LRT's for each model is larger than the critical value $\chi^2_{0.05(2)} = 5.99$. Thus, there is an evidence of heterogeneity of ANC care service visits across regions. It also observed that multilevel count regression model is best fit over the ordinary (single level) count regression models (Table 4.3).

Table 4.3 Likelihood ratio test value for multilevel and ordinary count model

	Multilevel Models					
Test	Poisson	NB	ZIP	ZINB	HP	HNB
LRT	2977.708	994.6363	677.1808	677.182	577.8368	577.8367

4.3.2 Testing the presence of correlation within the regions (Intra-class Correlation)

Intra Class Correlation (ICC) represents a measure of reliability, or dependence among individuals (Kreft & DeLeeuw, 1998). The ICC is a measure of the proportion of variation in the outcome variable that occurs between regions versus the total variation present. It ranges from 0 (no variance among clusters) to 1 (variance among clusters but no within-cluster variance). ICC can also be conceptualized as the correlation for the dependent measure for two individual mothers randomly selected from the same cluster (region).

Although a null model has no independent variables, it provides some useful information that will help us understand the structure of the data. In particular, the AIC and BIC values that are of primary interest in this case will be useful in comparing this model with others that include one or more independent variables, as we will see later. In addition, the null model also provides estimates of variance between region $\sigma^2_{u_0}$ and variance within a region σ^2_e . In turn, these values can be used to estimate ρ (ICC), as in Equation (25). Here, the value would be given in table 4.4:

Table 4.4 Testing the presence of correlation within the regions (Intra-class Correlation)

$\boldsymbol{\sigma^2_{u_0}}$	$\boldsymbol{\sigma^2_e}$
0.1805	2.19175

$$\boldsymbol{\rho = \frac{\sigma^2_{u_0}}{\sigma^2_{u_0} + \sigma^2_e} = \frac{0.1805}{0.1805 + 2.19175} = 0.0760881}$$

From the table 4.4, we interpret this value to mean that the correlation of number of antenatal care service visits among women within the same Region is 0.0761(7.61%). This result indicates very little correlation of number of antenatal care service visits showing there is no tendency for values from the same region to be similar and this also indicates that, Regions can be very reliably differentiated in terms of ‘ANC’ visits (when within correlation approaches to zero, between class correlation reliably differentiated in terms of the dependent variable).

4.3.3 Goodness of fit and criteria for model selection

Table 4.5 shows that deviance, AIC and BIC for model selection and fit criteria. A lower value of these criteria suggests a better fit. The results obtained indicate there is observed difference in values between the six models. Since multilevel HP regression model has smaller values in AIC, BIC and deviance, the multilevel hurdle Poisson regression model is better than the other models. In overall, all criteria revealed that the multilevel HP model predicted each count outcome very close to the observed counts.

Table 4.5 Model Selection Criteria for the Multilevel Count Regression Models

	Multilevel models					
Criteria	Poisson	NB	ZIP	ZINB	**HP**	HNB
AIC	28586.2	27094.0	24344.9	24346.9	**24235.9**	24337.9
BIC	28792.5	27307.2	24599.4	24608.3	**24290.4**	24599.3
Deviance	28526.2	27032.0	24270.9	24270.9	**24261.9**	24261.9

4.3.4 **Multilevel hurdle Regression Model**

4.3.4.1 Model Comparisons in Multilevel HP Model

The deviance, AIC and BIC values are used to select the best fitting model among the three fitted multilevel HP regression models. The deviance of the null model is **26981.3** and random intercept with fixed coefficient model is **24261.9.** These indicate that the random intercept with fixed coefficient model is better than the null model. And also, the deviance of the random coefficient model is 24341.1 which shows the random intercept with fixed coefficient model is better than the random coefficient model.

The AIC and BIC values of the model are used to make an overall comparison of the three models presented in Table 4.6. The computed AIC and BIC value for the random intercept is less than that of the random coefficient model and the empty model. This indicated that the random intercept model fits best compared to the intercept only model and random coefficient model.

Table 4.6 Summary results of multilevel HP model selection criteria

Criteria's	Intercept only model (null model)	**Random intercept with fixed coefficient model**	Random coefficient model
AIC	26987.3	**24235.9**	24383.1
BIC	27007.9	**24290.4**	24527.5
Deviance	26981.3	**24261.9**	24341.1

4.3.4.2 Random intercept-only model for multilevel hurdle Poisson model

The random intercept-only model would try to identify how much variation in between mothers' is due to differences between regions after we control for all our independent variables. The results from the model of random intercept-only model is given in the Table: 4.7.

Table 4.7 Results of random intercepts-only model of regional variations

	Conditional model(truncated count part)				
	Estimate	SE	z value	Pr(>|z|)	CI for estimate

	β				$\exp(\beta)$	Lower	upper
(Intercept)	1.33182	0.05942	22.41	<2e-16 *	3.7879	1.215	1.448
Random intercept -only ($\boldsymbol{\sigma_{u_0}}$)	0.0381	0.1952	15.2	<2e-16 *	1.0388	0.128	0.299
	Zero-inflation model:						
(Intercept)	-0.9723	0.3162	-3.075	0.0021 *	0.378	-0.353	-0.9723
Random intercept -only ($\boldsymbol{\sigma_{u_0}}$)	1.084	1.041	9.2	<2e-16 *	2.957	1.606	1.041

The result of the random intercept-only model shows that, there is significant variations at regional levels. On the other hand, the truncated count part of the result indicates that at the national level, on average, the expected number of ANC service visit per mother in the regions is about 3.7879.

4.3.4.3Results of the random intercept with fixed coefficient HP model

It is possible to generalize the model so that the effect of level-1 covariates is different in each region. In random intercept model, we allowed the intercept only to vary across regions by fixing explanatory covariates, But the relation between explanatory and dependent variables can differ between groups in many ways, for example, in the number of ANC visits per mother (nesting structure: mother within regions) it is possible that the effect of Distance from health facility on the number of ANC visits per mother is stronger in some regions than in others, this phenomenon is known as unobserved heterogeneity in the overall response of regression across Regions.

Firstly, hurdle Poisson model with random effects (mixed or multilevel HP) was carried out to account for both clustering and excessive zeros. The model is expected that it would explain the heterogeneity effects due to regional variations (level-2 units). As can be seen from the Table 4.8, number of antenatal care service visits per mother varies among the regions since the fact that variance of the random intercept, at region level (i.e $\boldsymbol{\sigma_{u_e}}^{\mathbf{2}}$**)** was found to be significant (P-value <2e-16 ***), Which indicated the number of antenatal care service visits per mother varies among regions of the country.

Table 4.8 Parameter estimates and standard errors for random intercept multilevel HP model

Estimation of Fixed effect count part							
Conditional model:							
Categories	Estimate β	Exp β	Std. Error	z value	Pr(>|z|)	CI for Estimates Lower	Upper
(Intercept)	1.207	3.343	0.048	25.147	< 2e-16 ***	1.113	1.301
PResidencUrban(Ref)	-----	--------	-------	-------	--------------	-------	------
PResidenceRural	-0.125	0.882	0.022	-5.735	9.78e-09 **	-0.168	-0.083
WI Poorest(Ref)	------	--------	-------	-------	--------	-------	--------
WI Poorer	0.089	0.915	0.026	3.432	0.000599 **	0.0382	0.1399
WIMiddle	0.102	1.107	0.027	3.858	0.000114 **	0.050	0.154
WIRicher	0.142	1.153	0.027	5.228	1.71e-07 **	0.088	0.1948
WIRichest	0.172	1.188	0.027	6.275	3.49e-10 **	0.118	0.226
HusbandELNo eduction(Ref)	-----	--------	-------	-------	-----------	--------	-----
HusbandELPrimary	0.022	1.022	0.020	1.094	0.273783	-0.018	0.062
HusbandELSecondary	0.091	1.095	0.025	3.558	0.000374 **	0.040	0.139
HusbandELHigher	0.158	1.171	0.027	5.822	5.83e-09 **	0.105	0.212
PregnancyNo(Ref)	----	--------	-------	-------	----------	---------	-------
pregnancyYes	0.131	1.14	0.016	7.979	1.48e-15 **	0.098	0.162
Estimation of Random effect truncated count part							
Region(Intercept) ($\boldsymbol{\sigma_{u_e}}$)	0.170	1.017	0.128	10.3	< 2e-16 ***	0.082	0.199
Estimation of Fixed effect Zero-inflation part							
	Estimate β	Exp(β)	Std. Error	z value	Pr(>|z|)	CI for Estimates Lower	Upper
(Intercept)	-0.814	0.443	0.287	-2.834	0.004599 **	-1.376	-0.251
Agec15-19(Ref)	-------	---------	---------	--------	-------------	------	---
Agec20-24	0.324	1.383	0.151	2.146	0.031836 *	0.028	0.620
Agec25-29	0.239	1.270	0.149	1.600	0.109683	-0.054	0.531

Agec30-34	0.244	1.276	0.154	1.585	0.113071	-0.058	0.545
Agec35-39	0.546	1.726	0.158	3.445	0.000572 **	0.235	0.856
Agec40-44	0.873	2.394	0.179	4.886	1.03e-06 **	0.523	1.222
Agec45-49	0.522	1.685	0.230	2.276	0.022849 *	0.072	0.972
PResidencUrban(Ref)	------	-------	--------	-------	-----------	-------	------
PResidenceRural	1.217	3.377	0.132	9.257	< 2e-16 ***	0.959	1.474
ELMNo edu(Ref)	-------	--------	---------	--------	----------	------	-------
ELMPrimary	0.520	1.68	0.081	-6.398	1.57e-10 **	-0.678	-0.360
ELMSecondary	0.557	1.75	0.182	-3.063	0.002191 **	-0.913	-0.201
ELMHigher	1.303	3.68	0.427	-3.049	0.002294 **	-2.140	-0.465
WIPoorer	0.665	1.94	0.089	-7.450	9.34e-14 **	-0.839	-0.489
WIMiddle	0.769	2.16	0.099	-7.784	7.01e-15 **	-0.963	-0.576
WIRicher	0.859	2.36	0.106	-8.082	6.39e-16 **	-1.067	-0.651
WIRichest	1.052	2.86	0.121	-8.701	< 2e-16 ***	-1.288	-0.815
HusbandENo eduction(Ref)	--------	---------	---------	--------	---------------	---------	-------
HusbandELPrimary	0.416	1.52	0.071	-5.821	5.86e-09 **	-0.556	-0.276
HusbandELSecondary	0.774	2.17	0.167	-4.638	3.51e-06 **	-1.101	-0.447
HusbandELHigher	0.882	2.41	0.127	-6.923	4.43e-12 **	-1.132	-0.632
FWTNot at all(Ref)	-------	---------	---------	--------	------------	-------	--------
FWTLess than once a week	0.252	1.29	0.122	-2.056	0.039745 *	-0.492	-0.012
FWTAt least once a week	0.346	1.42	0.177	-1.959	0.050148	-0.692	0.000
pregnancyNo(Ref)	------	---------	---------	------	----------	---------	---
pregnancyYes	1.205	3.336	0.071	17.037	< 2e-16 ***	-1.344	-1.067
WPThen(Ref)	------		---------	--------	------------	------	----
WPLater	0.140	1.150	0.091	1.547	0.121834	-0.037	0.318
WPNo more	0.527	1.694	0.110	4.803	1.56e-06 **	0.312	0.743

DistanceNo problem(Ref)	-------	-------	--------	--------	------------	-----	----
DistanceBig problem	-0.133	0.875	0.099	1.330	0.183503	-0.063	0.328
DistanceNot a big problem	-0.392	0.676	0.106	-3.702	0.000214 **	-0.599	-0.184
Estimation of random effect for zero inflated part							
Region(Intercept) (σ_{u_e})	0.390	1.477	0.625	8.38	<2e-16 ***	0.404	0.966
Key:- Ref : Reference categories and * indicates Significant values (P-value <0.05)							

The variance components model which we have just specified and estimated above assumes that the only variation between regions is in their intercepts. In order to study the covariates related with antenatal care service, we fitted the multilevel HP regression model with fixed coefficients to predict the count number of antenatal care visits per mother. The results from the random intercept model are given in Table 4.8. Variance components of random effects are observed in both between regions (region-level, σ_e^2) and between mothers (mother-level, σ_0^2) and it is significant (*p*-value = <2e-16 ***) and therefore we reject the null hypothesis of $\sigma_{u_e}^2 = 0$. This indicates that, the variation between regions is non zero regarding number of antenatal care service visits. The results of multilevel HP regression of random intercepts was identified that the covariates age, type of place of residence, wealth index, Mother educational level, husband educational level, frequency of watching television, distance from health facility, wantedness of pregnancy and pregnancy complication were found to be related with the antenatal care service follow-up and was showed to vary among regions of the country.

The “baseline” average antenatal care service visits from Poisson part is 3.343. The other exponentiated coefficients are interpreted multiplicatively. Mother living in rural area compared to average mother living in urban area decreases the average ANC visits by 0.882 time. Wealth indexes poorer, middle, richer and richest increases the average number of antenatal care service visits by 0.915, 1.107, 1.153 and 1.188 times respectively with reference to poorest.

Furthermore, there was also significant relationship between the antenatal care utilization and wealth index. Accordingly, the number of ANC follow-up increases as the mother’s economy increases .On the other hand, it indicated the likelihood antenatal care service visit increases as the educational level of a mother increases. According to the results, the number ANC follow up was higher for mothers with educational level of primary and above compared with mothers with no education.

The likelihood antenatal care service visit increases as the husband's educational level increases. Thus from the results, Husbands with educational level of primary ,secondary and higher increases the number of antenatal care service visits by 1.022, 1.095 and 1.171 compared to husbands with no education, respectively(from count part).

Controlling for the effects of other variables and allowing the intercept parameter to vary across regions, the likelihood of number of antenatal care service visits from mother of age groups 25-29 and 30-34 were 1.383 and 1.27 times higher as compared to the number of antenatal care service visits from mother of age groups 15-19, respectively. The estimated odds of number of antenatal care service visits among mother 40-44 age groups is 2.394 times higher than that of the estimated odds for the number of antenatal care service visits among mother 15-19 age group. The odds ratio for child-bearing mothers whose age of first pregnancy between 20 and 24 years equals exp(0.324)=1.383 ,which implies that those mothers whose age of first pregnancy between 20 and 24 years are 1.383 times more likely to visit ANC than those mothers whose age is between 15 and 20 years.

The rate ratio for child-bearing mothers having pregnancy complication during pregnancy equals exp(1.205) =3.336, which implies that those mothers having pregnancy complication were 3.336 times more likely visited than those mothers has no pregnancy complication.

The rate ratio for fertile aged mothers having big distance problems equals exp (-0.133)= 0.875 , which implies that those mothers having big distance problems are 0.875 times less likely to visit than those mothers has no distance problems.

4.3.4.4Model diagnostic checking

Residual interpretation for generalized linear mixed models (GLMMs) is often problematic. The point here is that misspecifications in GL(M)Ms cannot reliably be diagnosed with standard residual plots, and GLMMs are thus often not as thoroughly checked as LMs even if the model is correctly specified. The solution is simulating the quantile residuals. Diagnostic tools provided by the DHARMa package in R (Hartig, 2018) were used to evaluate the model fits. DHARMa simulates quantile residuals from a fitted GLMM that are standardized to values between 0 and 1. For a correctly specified model, these residuals should have a uniform distribution regardless of the underlying model structure, and can be interpreted similarly to residuals for linear models. The package includes statistical tests on the residuals to check for uniformity and zero inflation. There is also a function to plot the residuals against covariates in the model (or potential covariates not in the model) to look for possible misspecifications; for a correctly specified model, the residuals should be uniform in the y direction (i.e. flat with no systematic pattern with the covariates).

The plot of residuals versus fitted values is used to compare the residuals with the fitted values. There should be no relationship between these two values, so the LOWESS line should be horizontal and close to zero (Trexler & Travis, 1993). Figure 4.1 shows plots of the residuals vs. the fitted values. Plot of residuals versus fitted values of multilevel hurdle Poisson model has horizontal LOWESS lines with the lowest range of residual values.

Figure 4.1 shows Residual versus fitted value plot for final multilevel hurdle Poisson model and it does not show any systematic pattern which points out the model fits the data well.

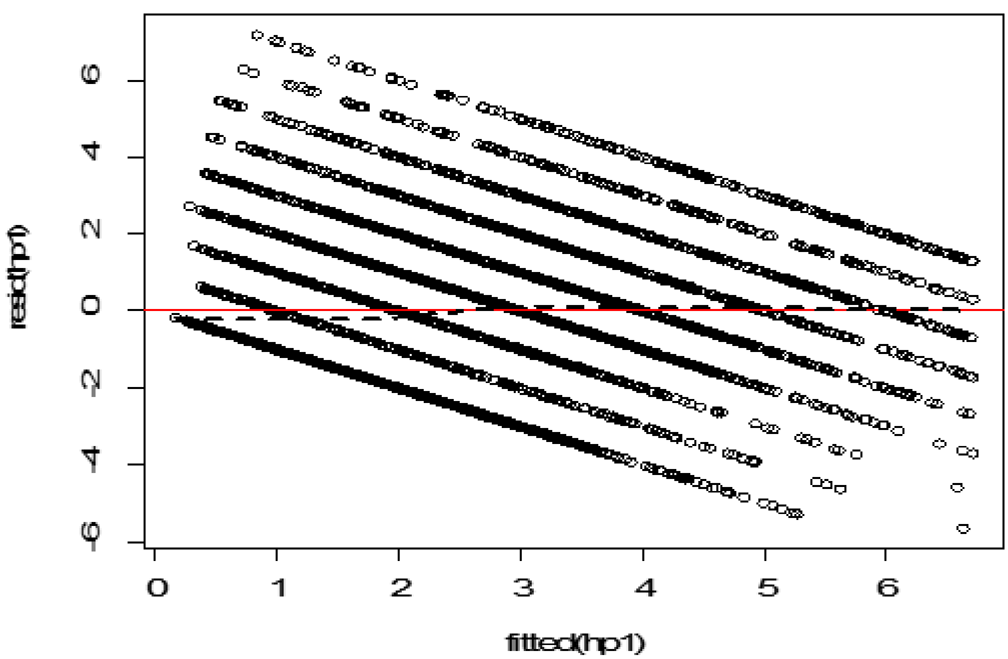
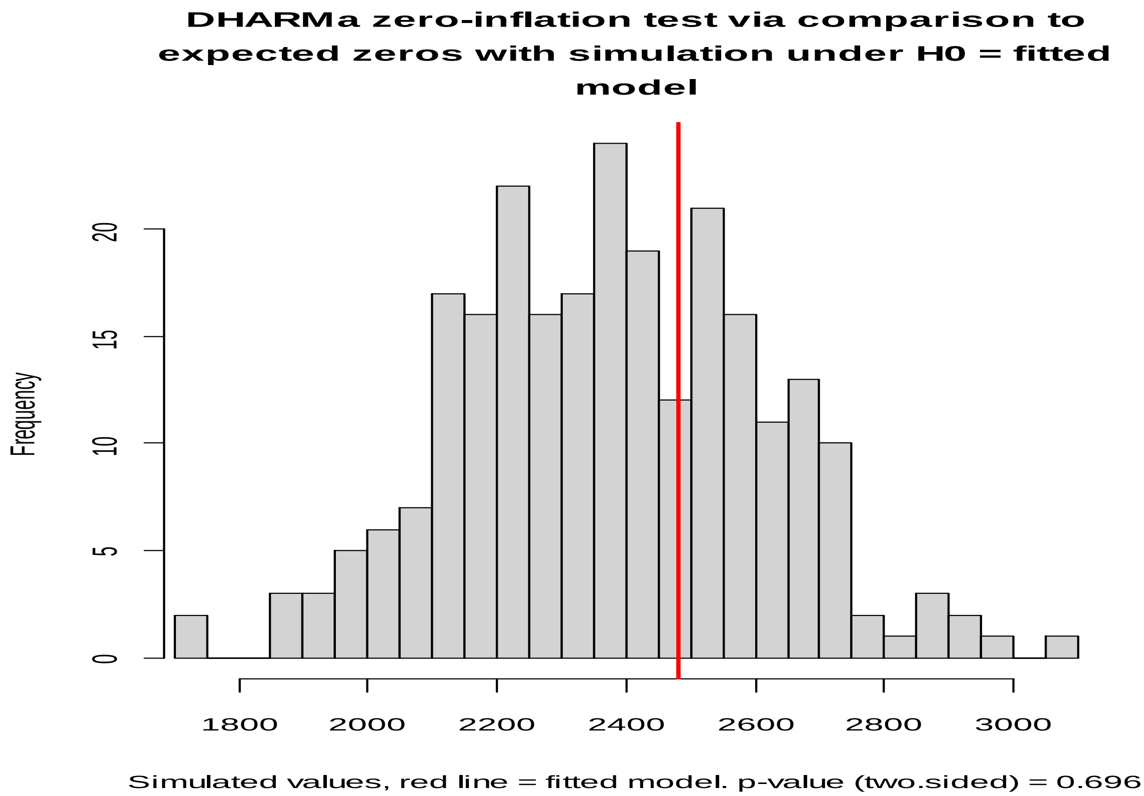


Figure 4.1 Fitted values vs. residual plots. LOWESS lines are dashed

Diagnostic plots for the multilevel hurdle Poisson model suggest that model fits the data well. The Q-Q plot to check for uniformity of the residuals if very close to linear which also supports the formal test (p=0.19928).no indication of lack of fit(figure 4.2, bottom). Zero-inflation test results(figure 4.2, top), showing the histogram of simulated test statistic values compared to the observed value from the fitted model (vertical red line); there is no evidence of zero-inflation in the residuals (p=0.696).



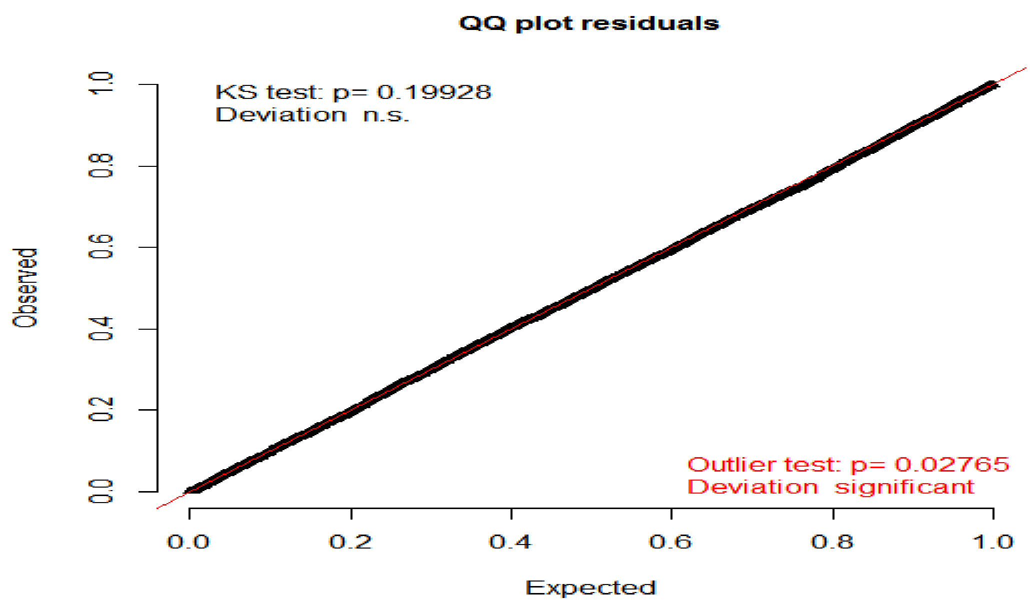


Figure 4.2 Diagnostic plots for testing uniformity and zero inflation in final fitted multilevel hurdle Poisson model.

4.3.5 Discussions of the Results

Using the EDHS data and an appropriate modeling approach, this study further assessed factors affecting number of ANC services visits in Ethiopia. Thus, this study has been attempted to identify Socio-demographic, Fertility related characteristics and ANC service related determinants of completing the recommended number of ANC service visits among pregnant women of reproductive age in Ethiopia by considering the clustered nature of the 2016 EDHS data set. The obtained results are discussed as follows.

This study indicated that, the number of ANC service was strongly influenced by mother's history of pregnancy complications. When mothers had a history of pregnancy complications, they were attending ANC service. This is agreed with the previous findings of studies that undertaken in Ecuador and Taiwan (Paredes I et al., 2005 and Liu TC et al. 2004). This is probably due to those women who experienced pregnancy complications before are more concerned about their health and better perceived the risk of pregnancy. As a result, they are more probably keen to seek medical care early and regularly.

Frequency of watching Television had a positive influence on women to utilize ANC service. Previously conducted studies in Ethiopia and Nigeria witnessed the influence of media exposure on ANC visits (Birmeta K et al., 2013 and Rai RK et al., 2012). The frequent promotion of maternal health services through media could influence women's predisposition for an early visit and their adherence to subsequent follow-ups by providing them with relevant information concerning the risk of pregnancy and the benefit of services.

Women's educational level was one of the strong predictor of attending ANC visit services follow-up in the study. This finding was consistent with a previous study done in Central Ethiopia which found that women with some education were more than twice more likely to attend ANC (OR=2.645) as compared with those who had no education (Birmeta K et al, 2013). Matsumura and Gubhaju study (Matsumura & Gubhaju, 2001) conducted in Nepal demonstrated that women with higher education were more likely to utilize ANC than those with lower education. A study carried out by Pallikadavath and others (Pallikadavath, Foss, & Stones, 2004) found similar results, in their study they had demonstrated that both maternal and paternal education positively influence utilization of ANC.

Another factor for attending number of ANC service visits in the country was type of place of residence. The study showed that women who lived in rural areas were less likely to receive services from skilled health personnel than urban resident women [AOR = 0.32281]. The chance of using ANC services was considerably reduced among women from the urban community to women from the rural community. This result was consistent with the finding of studies done in Vietnam, Ecuador and Nepalese (Tran TK et al., 2012, Paredes I et al., 2005 and Neupane S et al., 2012). This is most probably due to many social infrastructures; including health, education, transport, and information are highly concentrated in urban areas compared to rural areas. The best availability of these infrastructures in urban areas may have an important role in supporting women to develop a good health care seeking behaviors.

Wealth index was strongly and negatively associated with utilization of ANC services in Ethiopia. The study showed that poorest women were less ANC attendants than those of richest women. Similar results have been reported in the previous several studies in different countries. A study from Ethiopia identified that when women with higher incomes tend to start ANC early and the likelihood of utilizing ANC decreased, as the family income gets lower (Birmeta K et al, 2013).

Similarly, a study from China found that women who had higher household income were more likely to have sufficiently utilized ANC services (AOR=1.6, 95% CI=1.0-2.5) (Zhao QZJH, Yang S, Pan J, et al., 2012).

According to the study results, distance from health facility is an important socio-demographic predictor of antenatal care service visit attendance, that is, the number of ANC service visit decreases with increase in distance. This result in lined with the previous study that, distance to the health facility is inversely associated with ANC utilization (Glei et al., 2003a). This study was also consistent with the finding conducted by Magadi in Kenya (Magadi et al., 2004) which demonstrated an increase in distance to the nearest health care facilities was associated with fewer antenatal visits.

Regarding to this study, older women were more likely to have adequately utilized antenatal care rather than the younger. This finding is similar with previous several studies. Study from Central Ethiopia found that the odds of attending ANC are 1.2 times higher (OR=1.168) for women in the age group of 20-34 as compared to those in the age group 15–19 women (Birmeta K et al, 2013). Likewise, a study conducted in Vietnam found that older women (more than 25 years old) were more likely to utilize antenatal care (Tran TK et al., 2012). Similarly, a study conducted in China also found that women between the ages of 25 and 30 and women older than 30 were more likely to have adequately utilized antenatal care (AOR=2.2 and 1.9, 95%CI=1.4-3.5 and 1.1-3.2, respectively) than younger women (Yang S, et al., 2012)

Chapter five

5 Conclusions and Recommendations

5.1 Conclusion

The results of this study suggested the need to use individual level (mother) and region level disparities in the likelihood of number of ANC visits. This study found evidences that verify some Socio-demographic, Fertility related characteristics and ANC service related determinants considered in this study have significant influences on completing the recommended number of ANC visits among pregnant women of reproductive age in Ethiopia by considering the clustered nature of the data.

The study reported that only 65.4% of women in fertile age group in the country received ANC services at least once and 34.6% of women didn't received the ANC service. Among 7174 women in this study, only 255(3.6%) women received eight times or more (the recommended number of ANC contact).This figure showed underutilization of ANC services in the country as compared to the targeted number of ANC services visits.

From the exploratory results, we could identify that there was an excess zeros and high variability in the non-zero values. The variance of the number of ANC follow-up is larger than its mean, indicating that there is possibility of over dispersion. In addition, the over dispersion parameter is significantly different from zero in NB, ZINB as well as HNB models. This implies that standard Poisson model is not an adequate model to fit the number of antenatal service per mother. In this study, multilevel count regression models were used. There is an excess number of zeros and unobserved heterogeneity in the dataset.

In multilevel count regression analysis, individual mothers are considered as nested within the various regions in Ethiopia. As a first step in the multilevel approach, likelihood ratio test is applied to see if there are differences in number of ANC visits among the regions and test suggested that, the number of ANC visits varies among regions. Among the six multilevel count regression models, multilevel HP model is the best to account the heterogeneity of the number of antenatal care service visits per mother among regions of Ethiopia. From the three multilevel HP regressions models (null model, random intercept with fixed coefficient model and random coefficient model), the random intercept with fixed coefficient model provided the best fit for the number of ANC follow-up per mother. The results of multilevel HP regression of random intercepts was identified that the covariates age, type of place of residence, wealth index, Mother educational level, husband educational level, frequency of watching television, distance from health facility, wantedness of pregnancy and pregnancy complication were found to be related with the antenatal care service follow-up and was showed to vary among regions of the country. According to the results, it is possible to conclude that there are variations in terms of number of antenatal care service visits between regions and within a region.

5.2 Recommendations

Based on the findings of the study, we forwarded the following possible recommendations:

- The first recommendation will be, pregnant mother have to attend ANC service even though she had no pregnancy complication.
- The second recommendation will be education, which is a key strategic area to be addressed by the ministry of education of Ethiopian in improving women’s awareness towards ANC during a pregnancy.
- The third recommendation will be poverty reduction, which is another area of intervention that needs to be addressed by the concerned body of Ethiopian government.
- The fourth recommendation will be the expansion of infrastructure among the rural community needs to be prioritized by the concerned body of Ethiopian government, to improve ANC service utilization.
- The fifth recommendation will be the government of Ethiopia has to expand the media coverage related to ANC throughout the country including, and mothers have to be aware of the importance of ANC during pregnancy.
- The CSA is recommended to include variables which are discussed in literature review that may affect utilization of ANC visits.
- Finally, further researchers are recommended to conduct studies by taking three or four level count regression models into account to assess the variation of ANC service visits across enumeration area and regional level.

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APPENDIX (A)

A. Single-level Analysis

i. Variable Selection method

For the identification of determinant predictors of number of antenatal care visits at the first glance uni-variable analysis was performed using Poisson regression model and all the explanatory variables included in the model are chosen in advance with backward selection method was used to select variables before applying different count models. The results identified that: Region, place of residence, age, Educational level of mothers, Frequency of watching Television, wantedness of pregnancy and Distance were significant and the other variables are found to be non-significant and thus excluded from analysis. After Poisson regression model, the analysis using other count regression models (NB, ZIP, ZINB, HP and HNB) are used with variables selected using backward variable selection method under Poisson and NB.

ii. Goodness-of-fit and Test for dispersion

Turning first to the main effects model or model selection as shown in Table A1, the formal test of over dispersion in Poisson versus NB regressions H0: α = 0(no over dispersion in the dataset) vs H1: α > 0 there is over dispersion in the data set. Since, the likelihood ratio statistic 2*(-13934- -14252) = 636 with p-value=2.2e-16 ***, we reject the null hypothesis indicted that there was over-dispersion problems and the negative binomial model more appropriate than the Poisson model.

Table A1 Test for over dispersion

Criterion	Model	Value	p-value
LRT	NB	636	2.2e-16 ***

Also we can apply a formal statistical test of dispersion. Given $var(y_{i)} = \alpha\mu_i$, we test $H_0: \alpha = 1$ versus $H_1: \alpha > 1$. The chi-square test statistic is $\chi^2_{cal} = 1$ with P-value of 0. Thus, we reject the null hypothesis indicated that there was over-dispersion problems and the negative binomial model more appropriate than the Poisson model.

iii. Comparison between zero inflated Poisson and Negative Binomial

We use a likelihood ratio test to test if the added complexity of the zero-inflated Poisson model sufficiently improves the model to rationalize its use. The null hypothesis, Ho: is that the simpler model (the negative binomial) is better. The alternative hypothesis, HA, is that the more complex model (the zero-inflated Poisson) is better. The log-likelihood of the more complex model, the zero-inflated one, is -13934 and the log-likelihood of the simpler model, the negative binomial, is -13934. We take two times the difference of these models to find the t-statistic, 3347.6 .To find the p-value, we take 1−pchisq (t-statistic, difference in df). The p-value thus equals 2.2e-16 ***, and we conclude that the zero-inflated Poisson model has a significant improvement upon the negative binomial.

Table A2 Comparison between zero inflated Poisson and Negative Binomial

Modeles	Df	LRT	t- statistic	Pearson Chi-square	P-value
NB	47	-13934	3347.6	1	2.2e-16 ***
ZIP	36	-13934			

iv. Comparison between zero inflated Poisson and zero inflated Negative Binomial models.

The question might now be raised, which is better: the zero-inflated Poisson model, or the zero-inflated negative binomial model? We can perform another likelihood ratio test on these two models, with the formal hypotheses to test:

- Ho: The simpler model, the zero-inflated Poisson, should be selected in favor of the zero-inflated negative binomial model.
- HA: The zero-inflated negative binomial model (with an extra parameter for over dispersion), should be selected in favor of the zero-inflated Poisson model.

The log-likelihood of the more complex model, the zero-inflated negative binomial one, is -12260. The log-likelihood of the simpler model, the zero-inflated Poisson, is -12260 . We take two times the difference of these models to find the t-statistic, 0. To find the p-value, we take 1−pchisq (t-statistic, difference in df). The p-value thus equals 1. Therefore, we accept the null hypothesis and conclude that the zero-inflated Poisson model has a significant improvement upon the zero-inflated negative binomial.

a. Model Selection Criteria

i. Akaki Information Criteria values

Several model selection methods have been proposed in the literature. The most commonly used methods include information and likelihood based criteria. Six models described above are used to fit the data. AIC values and LRT for each model are presented in Table A3. The Poisson and

Negative binomial regression model had the largest AIC values demonstrating a poor fit to the data. Table A3 provides the computed values of AIC and likelihood ratio test for each models and we can use it to compare the goodness-of –fit of model. Further it indicates that ZIP and ZINB regression models were better fitted than Poisson and NB, respectively, based on their corresponding LRT as well as information criterion's. It was found that the model with the smallest AIC was considered as the best fit of the dataset. Since the LRT value for HP model and HNB model is -12406 and were insignificant (p-value =1) which accepts the null hypothesis of Ho: The simpler model, the Hurdle Poisson, should be selected in favor of the Hurdle negative binomial model. Therefore, it in turn supported by the Akaike information criteria obtained under each of the models. According to all these model selection criteria's, the HP model (small AIC) is identified as the best model which gives appropriate fit to the dataset than the other models.

Table A3 the computed AIC and LRT values for model comparison

Model	AIC	LRT
Poisson	28573.57	-14778
NB	27939.67	-14261
ZIP	24614.11	-12409
ZINB	24616.11	-12409
HP	**24289.63**	**-12406**
HNB	24291.63	-12406

ii. Vuong Test

To compare the performance of each model, we use Voung test as the models are non-nested (Vuong, 1989). The first comparison is made between the Poisson model and the ZIP model, with a Vuong test statistic of -37.729 and p =2.2e-16, implying that the ZIP model is preferred to the Poisson model for predicting the number of ANC per mother. The Vuong statistic for the NB versus ZINB (-44.537, p-value = 2.2e-16) favors the ZINB model. Hurdle negative binomial performed better than zero inflated negative binomial (Z=-2.558 *P-value* = 0.005271). After a series of tests and model comparisons, the HP model is preferred to ZIP regression mode (Z=-2.557, P=0.005272) (as shown in Table A4).Thus, we might select the HP model. The likelihood ratio test and AIC were also supported for the Hurdle model to fit the antenatal care service visits.

Table A4 voung test of the non-nested models

Model Comparison	Vuong test statistic	p-value	Preferable model
Poisson vs ZIP	-37.729	< 2.2e-16	ZIP
NB VS ZINB	-44.537	< 2.2e-16	ZINB
ZINB VS HNB	-2.558,	0.005271	HNB
ZIP VS HP	-2.557	0.005272	HP

iii. **Predicted value and Probability**

The result showed that the Poisson and the NB model under-estimated zero counts, the zero inflated models over-estimated zero counts and the hurdle models captured all zero values. Based on predicted outcomes, the differences in model fit between the six models are remarkable. Still the standard Poisson model and the NB model do not fit the data reasonably well (Table A5)

Table A5 Zero count capturing in count model

Number of zeros	**Observed**	**Poisson**	**NB**	**ZIP**	**NB**	**HP**	**HNP**
	2481	1051.374	1503.67	2476.139	2476.137	2481	2481

The plots of difference between predicted and observed values from each model against the observed value of the response was used to visualize how the model adequately expresses the response variable. In the following table, the values for observed and predicted probabilities for each model was presented. It indicated that, the values are very close to the observed values for both HP and HNB in predicting each count of ANC per mother.

Table A6 Values of observed and predicted probabilities.

No of ANC Visits	**Observed probabilities**	**Values of predicted probabilities**					
		Poisson model	NB model	ZIP model	ZINB model	HP	HNB
0	0.3458322	0.1464716	0.2097952	0.3462297	0.3462296	0.3458322	0.3458322
1	0.04767215	0.2274364	0.229618	0.06433148	0.06433084	0.06446052	0.06446051
2	0.07847784	0.2083789	0.1777989	0.1111646	0.111164	0.1113565	0.1113564
3	0.1654586	0.1524292	0.1230956	0.1316982	0.131698	0.1318694	0.1318693
4	0.1583496	0.1007039	0.08229958	0.1208263	0.1208266	0.1209161	0.1209160
5	0.08656259	0.06383838	0.05481668	0.09195245	0.09195287	0.09196002	0.09195997

6	0.05603568	0.03990759	0.03683968	0.06070483	0.06070521	0.06066569	0.06066573
7	0.02606635	0.02477341	0.02509194	0.03586879	0.03586904	0.03581866	0.03581875
8+	0.03554502	0.01520509	0.01733127	0.01939579	0.01939592	0.01935419	0.01935428

iv. Plots of Differences between Observed and Predicted value

Figure A1 provides the fit of Poisson, NB, ZIP, ZINB, HP and HNB models expressed by different colors. It showed that Poisson regression model gives poor fit to predict count of ANC per mother. On the other hand negative binomial regression model predicted 3's, 7's and 8's as strong as ZIP ZINB, HP and HNB regression models but it showed less predictions of other counts. The graph of ZIP, ZINB, HP and HNB regression models for the differences between predicted and observed values looks overlaid which mean that all four regression models efficiently predicted the count of ANC visits per mother.

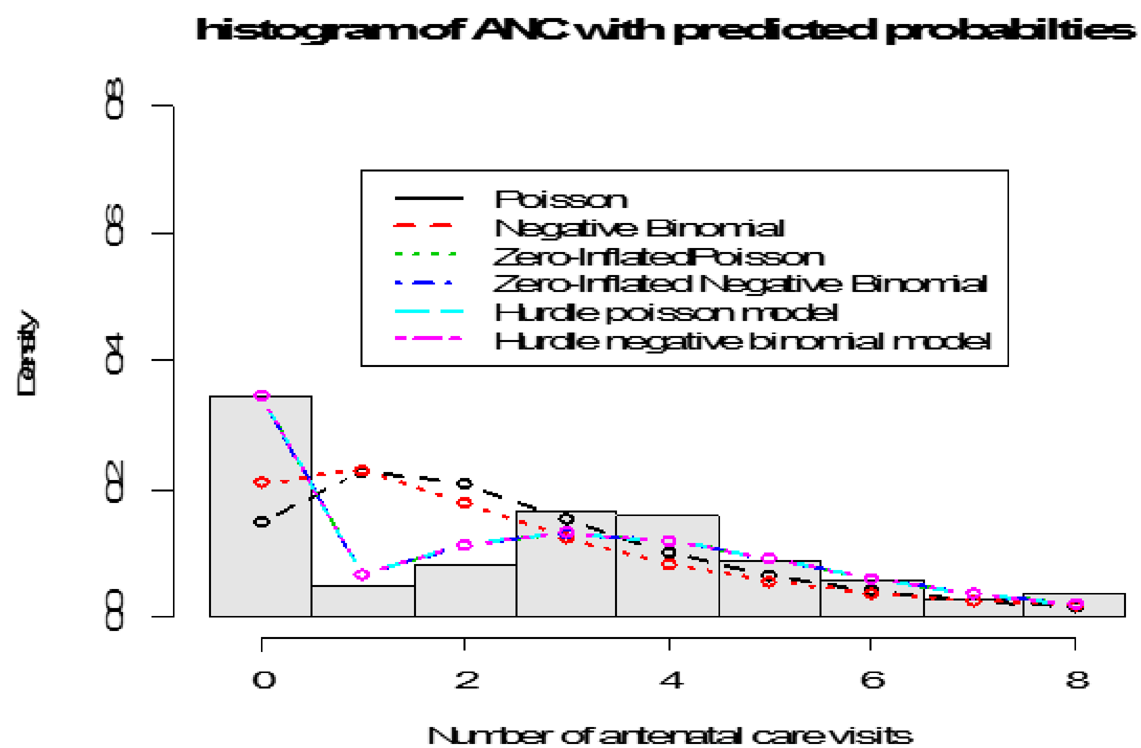


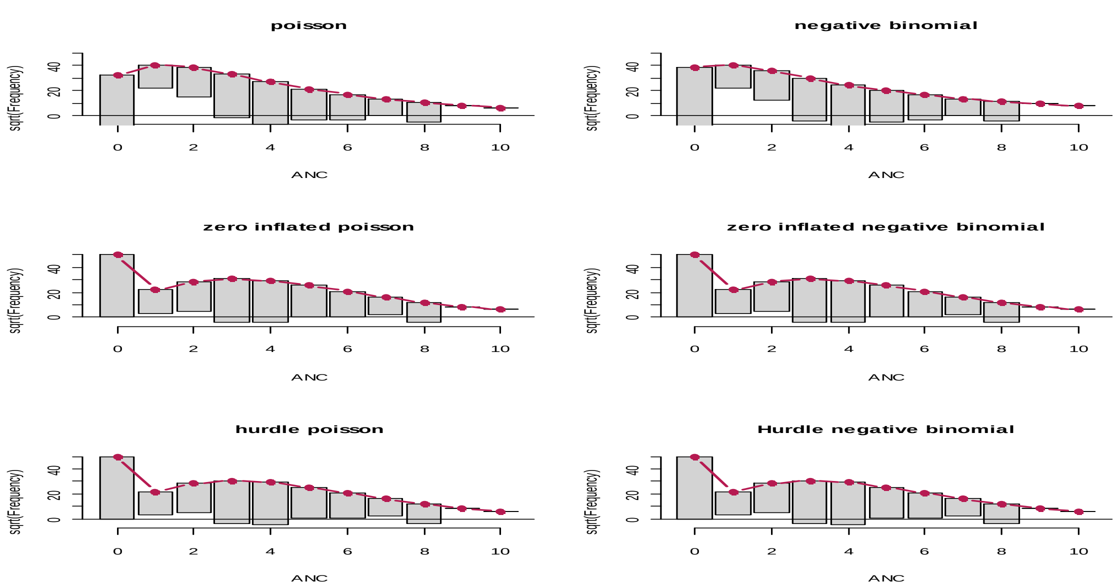
Figure A1 Histogram of number of ANC visits with overlaid predicted probabilities from each count regression models.

It also showed that the ZIP, ZINB, HP and HNB regression models account for the excess zeros quite well and all the four regression models reasonably capture the shape of the distribution of the relative frequencies. Clearly, a Hurdle model can account for the excess zeros and thus Hurdle Poisson (HIP) might be a solution because it can account for the excess zeros and it provides a more flexible estimator for the variance of the response variable.

b. Model diagnostic checking

It appears we have addressed the excess 0's, but what about the over dispersion? We can visualize the fit of this model using a rootogram. If a bar doesn't reach the zero line then the model over predicts a particular count bin, and if the bar exceeds the zero line it under predicts. The Poisson GLM is under predicted whilst some low counts are over predicted, and a large number of count bins are under predicted between 0 – 1 and 4-8 and over predicts between 1-2 counts. Focusing on the bottom of the bars we see an undulating pattern with runs either above or below the zero reference line, highlighting a general lack of fit in the model. Similarly, the rootogram for negative binomial model in figure A2 shows lack of fit.

From the rootogram for Hurdle model in figure A2 shows general good agreement between the expected and observed counts, with a small amount of over prediction of some counts between 1–2. The fit of the Poisson GLM to data generated using a ZIP, ZINB and HNB also shows considerable good fit similar to the Hurdle model.



FigureA2: rootogram to visualize the fit of Hurdle model.

Another plot that is useful to examine is to compare the residuals to the predicted values. There should be no relationship between these two values, so the LOWESS line should be horizontal and close to zero (Trexler & Travis, 1993). Figure A3 shows plots of the residuals vs. the predicted values and has horizontal LOWESS lines, with the Hurdle model having the lowest range of residual values.

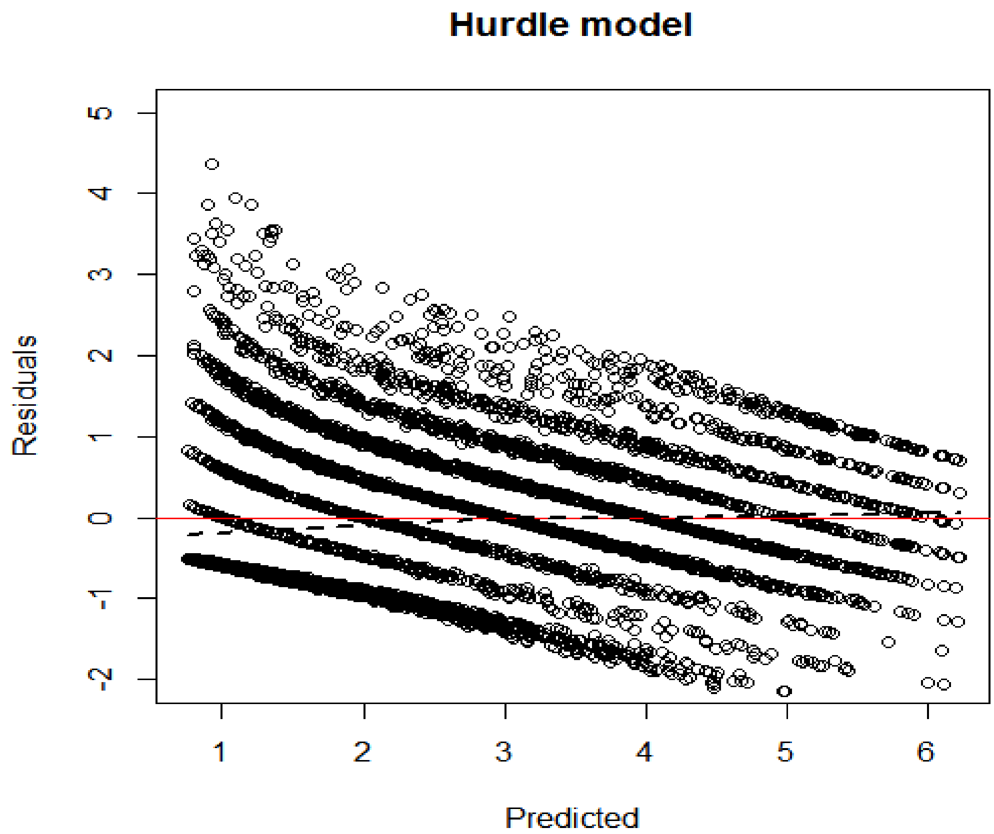


Figure A3 Predicted values vs. residual plots. LOWESS lines are dashed

The plots of the predictor variables against the standardized residuals are shown in Figure A4. Based on visual inspection, we determined that the residual distributions were approximately the same across levels of the predictor variables. On the whole, the residual patterns across all predictor variables from the Hurdle model were acceptable.

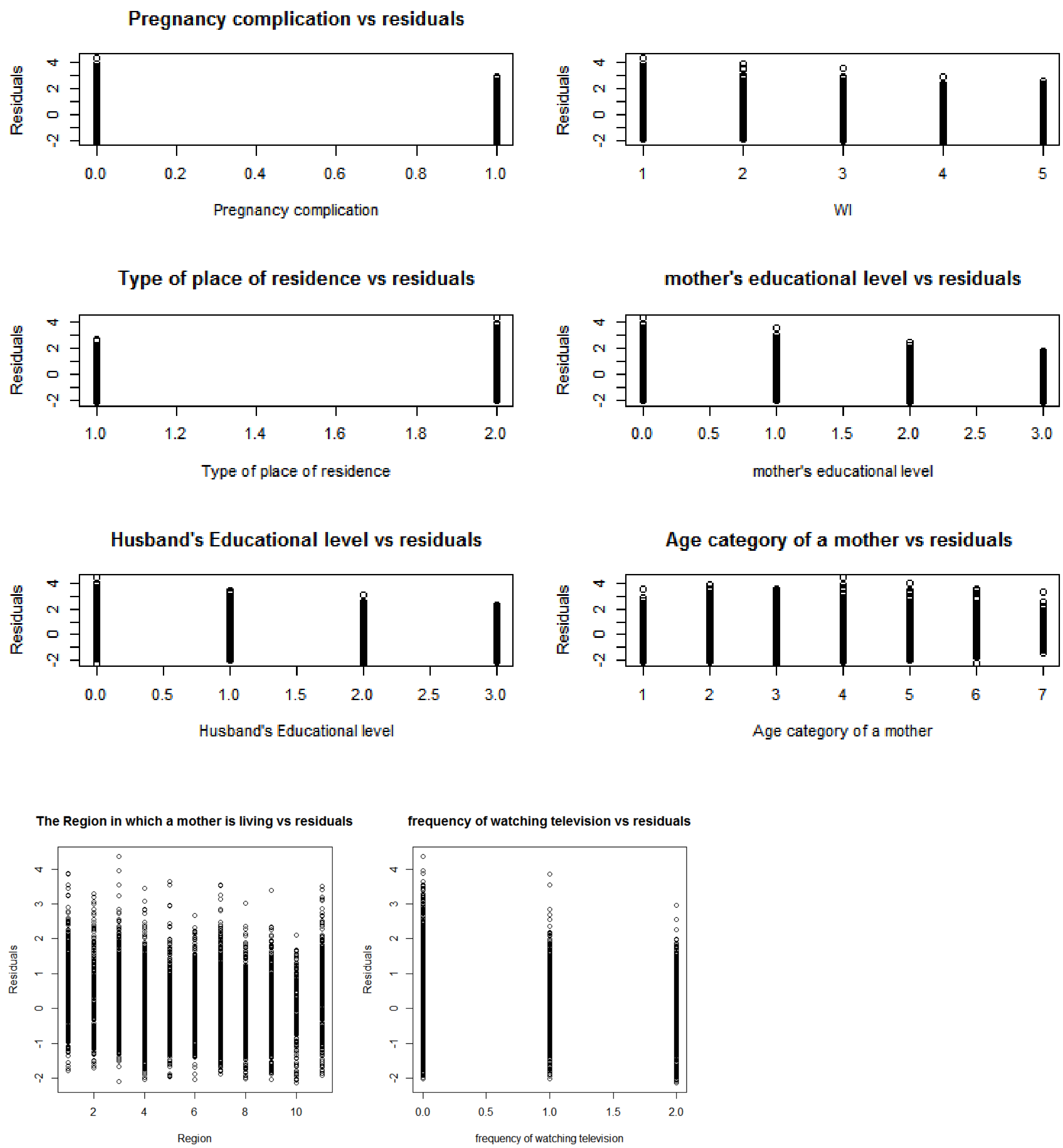


Figure A4. Plots of Hurdle model predictors vs residuals.

As a final check we can also look at the Q-Q plot of the quintile residuals in the hurdle model. These look fairly normal and show no suspicious departures from the model.

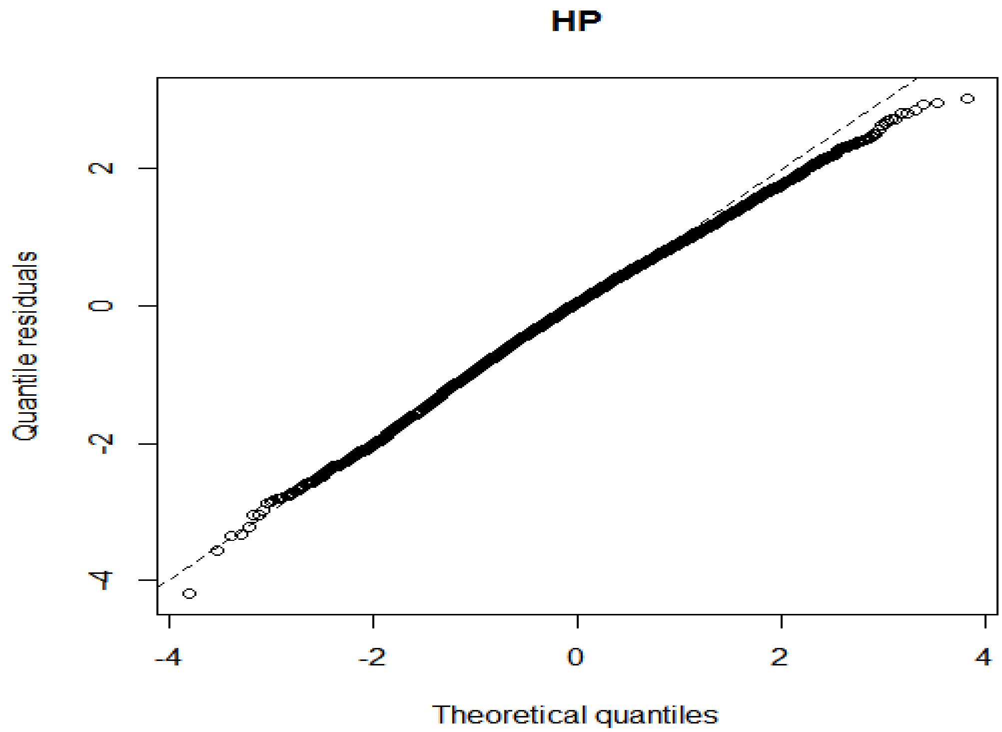


Fig A5 the Q-Q plot of the quintile residuals in the hurdle model

v. Interpretation of the results from hurdle poison regression model

It turned out that the HP model with region, frequency of watching television, wealth index, type of place of residence, pregnancy complication, husband educational level, age of the mother, educational level of mother, and distance from health facility as covariates was the most parsimonious model. Based on the above mentioned criteria for model selection and evaluation, especially, Vuong test, AIC and log-likelihood, we selected hurdle Poisson model for fitting the number ANC per women dataset. The cumulative evidence suggested that the hurdle model provided an adequate fit to the data than ZIP, ZINB and HNB model for the dataset. Based on the results of all models, it is reasonable to assume that the standard errors of the HP model's parameter estimates are unbiased and that the model's estimates are suitable for statistical inference.

Table A7 Estimates of the model with Exponentiated coefficients and their standard errors of HP regression

Count model coefficients (truncated poisson with log link):							
Variable categories	β (Estimates)	Exp(β)	Std. Error	z value	Pr(>|z|)	CI for β	
						Loweer	Upper
(Intercept)	1.22200	3.39396	0.03799	32.164	< 2e-16 ***	1.148	1.296
RegionTigray(Ref)	-------	------	-------	------	---------	-----	------
RegionAfar	-0.10870	0.89699	0.04206	-2.584	0.009755 *	-0.191	-0.026
RegionAmhara	- 0.06551	0.93659	0.03237	-2.024	0.043006 *	-0.129	-0.002
RegionOromia	-0.11408	0.89218	0.03250	-3.511	0.000447 *	-0.178	-0.050
RegionSomali	-0.25593	0.7742	0.04079	-6.274	3.53e-10 **	-0.336	-0.176
RegionBenishangul	-0.04581	0.95522	0.03466	-1.322	0.186330	-0.114	0.022
RegionSNNPR	-0.03298	0.96755	0.02988	-1.104	0.269594	-0.092	0.026
RegionGambela	-0.03030	0.97016	0.03708	-0.817	0.413972	-0.106	0.042
RegionHarari	-0.10629	0.89916	0.03693	-2.878	0.004001 *	-0.179	-0.034
RegionAddis Adaba	0.20961	1.2332	0.03472	6.036	1.58e-09 **	0.142	0.278
RegionDire Dawa	0.21809	1.24369	0.03361	6.489	8.64e-11 **	0.152	0.284
PResidenceUrban(Ref)	------	----	----	----	-----	--------	
PResidenceRural	-0.10518	0.90016	0.02567	-4.097	4.18e-05 **	-0.155	-0.055
FWTLess than once a week	0.04845	1.04965	0.02697	1.797	0.072385	-0.004	0.101
FWTNot at all(Ref)	-------	-------	-------	------	--------	--------------	
FWTAt least once a week	0.02570	1.02602	0.02776	0.926	0.354601	-0.029	0.081
WIPoorest(Ref)	-------	--------	--------	-------	----------	----------------	
WIPoorer	0.08388	1.0875	0.02609	3.215	0.001306 *	0.033	0.135
WIMiddle	0.09397	1.09853	0.02705	3.474	0.000513 *	0.041	0.147
WIRicher	0.13134	1.14035	0.02787	4.713	2.44e-06 **	0.077	0.186
WIRichest	0.15857	1.17184	0.02878	5.510	3.59e-08 **	0.102	0.215
pregnancyNo (Ref)	------	-------	------	------	--------	-------	

pregnancyYes	0.12894	1.13762	0.01632	7.899	2.82e-15 **	0.097	0.161
HusbandELNo educti(Ref)	--------	--------	--------	-------	---------	--------	
HusbandEL Primary	0.01966	1.01986	0.02049	0.960	0.337236	-0.020	0.056
HusbandEL Secondary	0.08635	1.09018	0.02537	3.404	0.000665 *	0.037	0.136
HusbandEL Higher	0.15369	1.16613	0.02741	5.608	2.05e-08 *	0.099	0.207
Zero hurdle model coefficients (binomial with logit link):							
Variable categories	β (Estima es)	Exp(β)	Std. Error	z value	Pr(>|z|)	CI for β	
						Lower	Upper
(Intercept)	0.42655	1.5319	0.20488	2.082	0.037348 *	0.025	0.828
Agec15-19 (Ref)	--------	-------	------	------	---------	-------	
Agec20-24	-0.25275	0.7766	0.14686	-1.721	0.085253	-0.541	0.035
Agec25-29	-0.15771	0.8541	0.14466	-1.090	0.275610	-0.441	0.126
Agec30-34	-0.15711	0.8546	0.14853	-1.058	0.290179	-0.448	0.134
Agec35-39	-0.39274	0.6752	0.15242	-2.577	0.009972 *	-0.691	-0.094
Agec40-44	-0.61460	0.5408	0.17145	-3.585	0.000338 *	-0.951	-0.279
Agec45-49	-0.39316	0.6749	0.22077	-1.781	0.074941	-0.826	0.040
PResidenceUrban(Ref)	--------	--------	---------	--------	-----------	------	
PResidenceRural	-1.13070	0.3228	0.12394	-9.123	< 2e-16 **	-1.374	-0.888
ELMNo eduction (Ref)	-------	------	--------	-------	--------	------	
ELMPrimary	0.54416	1.72317	0.07731	7.039	1.94e-12 *	0.393	0.696
ELMSecondary	0.53775	1.7121	0.17261	3.115	0.001838 *	0.199	0.876
ELMHigher	1.27803	3.5895	0.41794	3.058	0.002229 *	0.459	2.0972
FWTLess than once a week	0.27280	1.3136	0.11870	2.298	0.021545 *	0.040	0.505
FWTNot at all(Ref)	------	-------	--------	-------	--------	----------	
FWTAt least once a week	0.42485	1.5293	0.16940	2.508	0.012142 *	0.093	0.757

WIPoorest(Ref)	------	---------	--------	-------	-------------	----------
WIPoorer	0.78518	2.1927	0.07995	9.821	< 2e-16 ***	0.628 0.942
WIMiddle	0.86280	2.3697	0.08747	9.864	< 2e-16 ***	0.691 1.034
WIRicher	0.84473	2.3273	0.09449	8.940	< 2e-16 ***	0.660 1.030
WIRichest	0.99644	2.7086	0.10893	9.147	< 2e-16 ***	0.783 1.210
DistanceNo problem(Ref)	--------	--------	-------	-----	--------------	-----------
DistanceBig Problem	-0.12628	0.8813	0.09607	-1.314	0.188714	-0.315 0.062
DistanceNot a big problem	0.43988	1.5525	0.10167	4.327	1.51e-05 **	0.241 0.639
pregnancyNo(Ref)	-----------	---------	---------	--------	------------	-------
pregnancyYes	1.25914	3.5223	0.06850	-18.381	< 2e-16 ***	1.125 1.393
HusbandELNoedu(Ref)	--------	--------	--------	-------	---------	-----
HusbandELPrimary	0.46174	1.586	0.06732	6.859	6.95e-12 **	0.330 0.594
HusbandELSecondar	0.84567	2.3295	0.12251	6.903	5.10e-12 **	0.606 1.086
HusbandELHigher	0.75095	2.1190	0.15840	4.741	2.13e-06 *	0.440 1.061
WPThen (Ref)	----------	---------	--------	------	-------	----
WPLater	-0.09668	0.9078	0.08729	-1.108	0.268020	-0.268 0.074
WPNo more	-0.52624	0.5908	0.10555	-4.986	6.17e-07 **	-0.733 -0.319
Key:- Ref : Reference categories and * is Significant (P-value <0.05)						

In order to study the covariates related with antenatal care service, we fitted the HP regression model to predict the count number of antenatal care visits per mother. The predictors related to ANC among those in Poisson part of the model such as region, frequency of watching television, wealth index, and type of place of residence, pregnancy complication and husband educational level were identified as statistically significant. And also in logistic part (zero hurdle model) of the model, age of the mother, educational level of mother, wealth index, frequency of watching television, type of place of residence, pregnancy complication, Husband educational level, wantedness of pregnancy and distance from health facility were identified as statistically significant in addition to the Poisson part.

The “baseline” average antenatal care service visits Poisson part is 3.39396. The other exponentiated coefficients are interpreted multiplicatively. One unit increase to live in Addis Ababa and Dire Dawa city administrations increases the average number of antenatal care service visits by 1.2332 and 1.24369 times respectively whereas one unit increase to live in Afar, Amhara, Oromiya, Somali, Bendhangul, SNNPR, Gambella and Harari decreases the average number of antenatal care service visits by 0.89699, 0.93659, 0.89218, 0.7742, 0.953589, 0.962113, 0.97016 and 0.89916 times respectively with respect to Tigray region. Mother living in rural area compared to average mother living in urban area decreases the average ANC visits by 0.90016 time. One unit increase in wealth indexes poorer, middle, richer and richest increases the average number of antenatal care service visits by 1.0875, 1.09853, 1.14035 and 1.17184times respectively with reference to poorest.

APPENDIX (B)

Table B1 parameter estimation for multilevel Poisson and Multilevel negative binomial regression models of random intercept with fixed coefficients.

	Multilevel Poisson		Multilevel negative binomial	
Coefficients	Estimates	SE	Estimates	SE
Intercept	0.53611*	0.08396	0.43284 *	0.10063
Agec15-19(Ref)	-----------	----------	-------------	-------------------
Agec20-24	-0.07563*	0.03695	-0.08766	0.05066
Agec25-29	-0.02889	0.03642	-0.03356	0.04993
Agec30-34	-0.02192	0.03777	-0.02936	0.05186
Agec35-39	-0.09439*	0.03944	-0.10304	0.05427
Agec40-44	-0.16358 *	0.04712	-0.19977*	0.06594
Agec45-49	-0.13792*	0.06771	-0.14831	0.09556
PResidenceUrban(Ref)	--------	---------	-----------	----------
PResidenceRural	-0.25819*	0.02603	-0.28469 *	0.03615
ELMNo edu(Ref)	------------	-----------	-----------------	---------------
ELMPrimary	0.14734*	0.02008	0.18626 *	0.02796
ELMSecondary	0.10520 *	0.02954	0.13124 *	0.04062
ELMHigher	0.05700*	0.03712	0.08276	0.05056
FWT not at all(Ref)	-------------	-----------	---------------	-------------
FWTLess than once a week	0.06797 *	0.02631	0.05887	0.03645
FWTAt least once a week	-0.01076	0.02745	-0.01929	0.03775
WIPoorest(Ref)	------------	------------	-------------	----------
WIPoorer	0.30579 *	0.02511	0.37416 *	0.03590
WIMiddle	0.32122 *	0.02620	0.39133 *	0.03736
WIRicher	0.36435*	0.02716	0.43590*	0.03859
WIRichest	0.42031*	0.02854	0.49675*	0.04032
DistanceNo problem	-------------	------------	------------	-----------
DistanceBig problem	-0.02249	0.02658	-0.04338	0.03689
DistanceNot a big problem	0.11636*	0.02592	0.12309 *	0.03577
pregnancyNo	------------	----------	---------	---------
pregnancyYes	0.36010*	0.01581	0.41416 *	0.02220
HusbandELNo edu(Ref)	---------------	-------------	------------	-------------
	0.16979*	0.02018	0.21532 *	0.02858

HusbandELPrimary	0.26828 *	0.02622	0.31367*	0.03671
HusbandELSecondary	0.32912*	0.02935	0.37003*	0.04086
HusbandELHigher	-------------	------------	-------------	-------------
WPThen (Ref)	-0.04464 *	0.02140	-0.05003 *	0.02951
WPLater	-0.14063*	0.02971	-0.17328	0.04204
WPNo more				
Estimation of Random effect				
Between-region variance $(\sigma_{u_e}{}^2)$	0.04729 *	0.2175	0.05273 *	0.2296
Key:- Ref : Reference categories and * indicates Significant values (P-value <0.05)				

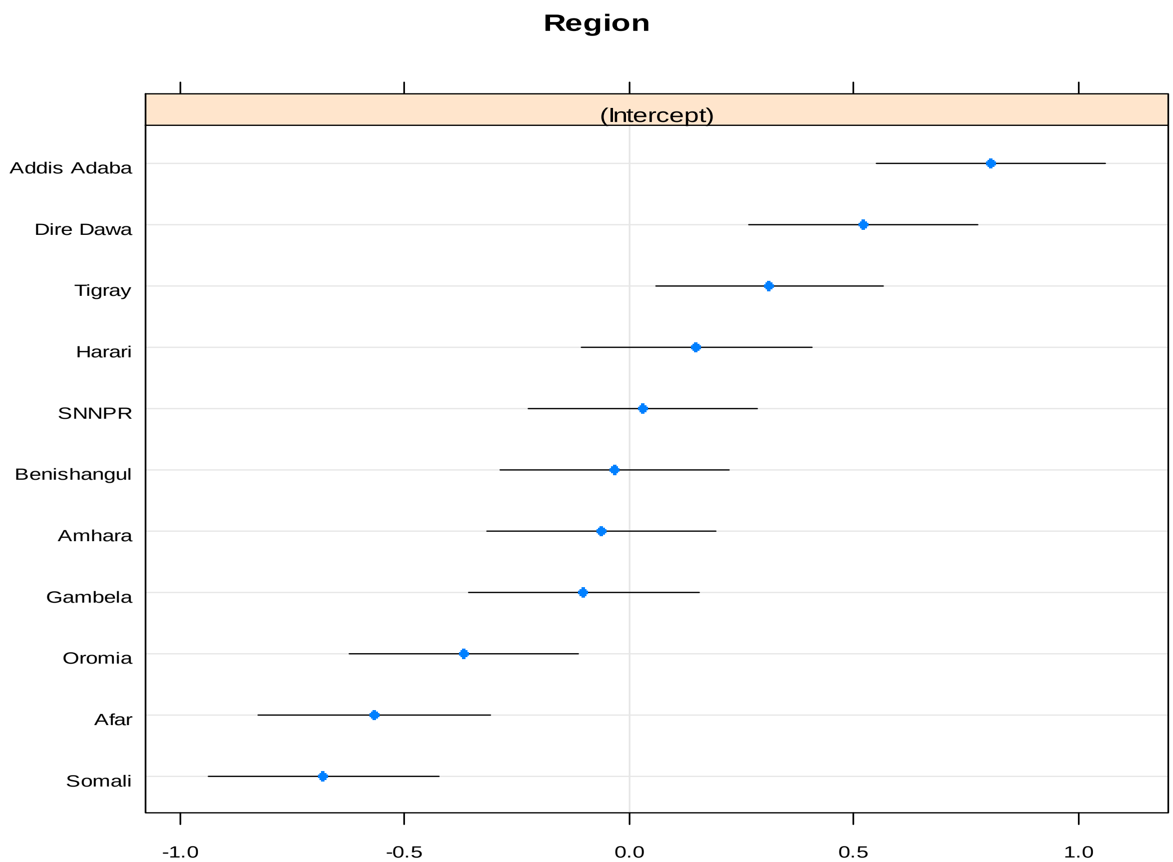
Table B2 Parameter estimation for multilevel ZIP, ZINB, HP and HNB models of random intercepts model with fixed coefficients

Coefficients	**Multilevel ZIP**		**Multilevel ZINB**		**Multilevel HP**		**Multilevel HNB**	
	Count part							
	Estimates	SE	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	1.20151*	0.04765	1.20161*	0.0476	1.2074 *	0.0480	1.2074 *	0.048
PResidenceUrban(Ref)	-----------	---------	----------	-------	---------	---------	--------	------
PResidenceRural	-0.1238 *	0.02173	-0.1238*	0.0217	-0.1252*	0.0218	-0.1252*	0.022
WIPoorest(Ref)	------------	---------	----------	-------	---------	------	---------	------
WIPoorer	0.09178*	0.02581	0.09176*	0.0258	0.08904*	0.026	0.08904*	0.026
WIMiddle	0.10607*	0.02640	0.10605*	0.0264	0.1024*	0.0265	0.1024*	0.027
WIRicher	0.14450*	0.02699	0.14446*	0.0271	0.14173*	0.0271	0.14173*	0.027
WIRichest	0.17448*	0.02727	0.1745 *	0.0273	0.17202*	0.0274	0.17202*	0.027
HusbandELNo educti(Ref)	------------	---------	---------	---------	---------	------	----------	-----
HusbandELPrimary	-0.0232	0.02033	0.02310	0.0203	0.02236	0.0204	0.02236	0.020
HusbandELSecondary	0.09088*	0.02511	0.09088*	0.0251	0.08986*	0.0253	0.08986*	0.025
HusbandELHigher	0.15920*	0.02701	0.15920*	0.0270	0.15830	0.0272	0.15830	0.027
pregnancyYes	0.13701*	0.01633	0.13700*	0.0163	0.1301 *	0.0163	0.1301 *	0.016
Estimation of Random effect for count part								
Between-region variance $(\sigma_{u_e}{}^2)$	0.0161*	0.1269	0.01609*	0.1268	0.01639*	0.128	0.01639 *	0.128

Logistic Part								
(Intercept)	-1.0476*	0.31461	-1.0472*	0.3146	-0.8136*	0.2871	0.81329*	0.287
Agec15-19(Ref)	----------	---------	---------	-------	---------	---------	--------	------
Agec20-24	0.3821 *	0.16910	0.38188*	0.1691	0.3244*	0.1511	0.32424*	0.151
Agec25-29	0.30033	0.16675	0.30008	0.1667	0.23871	0.1492	0.23845	0.149
Agec30-34	0.2967	0.1714	0.29627	0.1714	0.24367	0.1538	0.24347	0.154
Agec35-39	0.6277*	0.17588	0.62729*	0.1759	0.54573*	0.1584	0.54548 *	0.158
Agec40-44	0.96891*	0.19625	0.96866*	0.1962	0.8726*	0.1786	0.87237*	0.179
Agec45-49	0.59903*	0.24758	0.59874*	0.2476	0.52245*	0.2296	0.52236 *	0.231
PResidenceUrban(Ref)	------------	----------	----------	--------	----------	-------	--------	------
PResidenceRural	1.31533*	0.15356	1.31541*	0.1536	-1.2168*	0.1315	1.21658*	0.132
ELMPrimary	-0.5734 *	0.08985	-0.5731*	0.0898	0.5197*	0.0812	-0.51970*	0.081
ELMSecondary	-0.5936*	0.20565	-0.5939*	0.2056	0.5570*	0.1819	-0.55733*	0.182
ELMHigher	-1.3694*	0.51184	-1.3701*	0.5119	1.3028*	0.4273	-1.30332	0.427
WIPoorest(Ref)	-----------	----------	---------	-------	---------	------	----------	-----
WIPoorer	0.6703*	0.09734	0.6701*	0.0973	0.6645*	0.0892	0.66432	0.089
WIMiddle	0.7731*	0.10793	0.7725*	0.1079	0.7694*	0.0989	0.76923	0.099
WIRicher	0.8547*	0.11542	0.8544*	0.1154	0.85888	0.1063	0.85882	0.107
WIRichest	1.0510*	0.13178	1.0511*	0.1318	1.0516*	0.1209	1.05179	0.121
HusbandELNo edu(Ref)	------------	----------	-----------	--------	---------	-------	---------	----
HusbandELPrimary	0.4354*	0.07792	0.4354*	0.0779	0.4158*	0.0714	0.41599	0.072
HusbandELSecondary	0.7650*	0.14394	0.7645*	0.1439	0.7738*	0.1274	0.88227	0.127
HusbandELHigher	0.9252*	0.18508	0.9248*	0.1851	0.8822*	0.1668	0.77408	0.167
FWTNot at all(Ref)	-----------	-------	----------	-------	----------	--------	--------	-----
FWTLess than once a week	0.2861*	0.13616	0.2854*	0.1361	0.2517*	0.1224	0.25205	0.122
FWTAt least once a week	0.4201*	0.21038	0.4201*	0.2104	0.34609	0.1767	0.34617	0.177
pregnancyNo(Ref)	----------	------	---------	---------	--------	-------	-------	-----
pregnancyYes	1.2175*	0.07812	-1.2172*	0.0781	1.2053*	0.0708	1.20531	0.071
WPThen(Ref)	------------	---------	---------	-------	---------	-------	----------	----
WPLater	0.15838	0.09790	0.1586	0.0979	0.14028	0.0907	0.14023	0.091
WPNo more	0.57002*	0.11699	0.5702*	0.1171	0.52742*	0.1098	0.52727	0.110
DistanceNo problem	-----------	--------	---------	--------	----------	--------	---------	-----
DistanceBig problem	0.13503	0.10673	0.1348	0.1067	0.13261*	0.0997	0.13268	0.099

DistanceNot a big problem	-0.4312*	0.11436	-0.4315*	0.1144	-0.39191	0.1059	-0.39178	0.106
Estimation of random effect for logistic part								
Between-region variance ($\sigma_{u_e}{}^2$)	0.437*	0.6611	0.4368 *	0.6609	0.3902*	0.6247	0.3903	0.625
Key:- Ref : Reference categories and * indicates Significant values (P-value <0.05)								

Fig B1 let's check the diagnostics for the random effects:



This looks OK: no sign of discontinuous jumps (indicating possible multi-modality in random effects) or outlier Regions.

Figure B2 plots of effects of conditional predictor variables