ADDIS ABABA UNIVERSITY

DEPARTMENT OF STATISTICS

MULTILEVEL REGRESSION ANALYSIS OF RISK COVARIATES ASSOCIATED WITH WASTING AMONG ETHIOPIAN CHILDREN

BY

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This is to certify that the thesis prepared by Erko Sufa, entitled: Multilevel Regression Analysis of Risk Covariates Associated with Wasting Among Ethiopian Children and submitted in partial fulfillment of the requirements for the Degree Master of Science in Statistics (Biostatistics) compiles with the regulations of the University and meets the accepted standards concerning originality and quality. Signed by the examining committee:

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Advisor___________________________________signature___________Date__________

Declaration

I, the undersigned, declare that the thesis is my original work, has not been presented for degrees in any other university and all sources of materials used for the thesis have been duly acknowledged.

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This thesis has been submitted for examination with my approval as a university advisor.

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Abbreviations and Acronyms

ADB	African Development Bank
AIC	Akaike Information Criterion
ALF	African Leaders for Nutrition
AOR	Adjusted Odds Ratio
BIC	Bayesian Information Criterion
BMI	Body Mass Index
COHA	Cost of Hunger in Africa
CSA	Central Statistical Agency
DHS	Demographic Health Survey
DBF	Duration of Breast Feeding
EA	Enumeration Area
EMDHS	Ethiopian Mini Demographic Health Survey
EPHI	Ethiopian Public Health Institute
ETB	Ethiopia Birr
GDP	Growth Domestic Product
GNR	Global Nutrition Report
HH	Household
IFC	International Finance Corporation
ML	Maximum Likelihood
NIH	National Institute of Health
POM	Proportional Odds Model
SAM	Severe Acute Malnutrition
USAID	United States Agency for International Development
UNICEF	United Nations Children's Fund
WHO	World Health Organization

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Abstract

Multilevel Regression Analysis of Risk Covariates Associated with Wasting Among Ethiopian Children

Wasting is defined as low weight-for-height. It often indicates recent and severe weight loss, although it can also persist for a long time. Wasting in children is associated with a higher risk of death unless treated properly. The overall aim of the study was to assess risk covariates associated with wasting among children in Ethiopia. The source of data is Ethiopia mini DHS data undertaken in 2019. The DHS program employed a multistage sampling method. A total of 5164 children under five from the nation were included in this study. Descriptive (weighted frequency table and percentage) and inferential (multilevel proportional odds model) statistical methods were employed. The descriptive results show that 92.75% of under-five children were normal, 6.06% were moderately wasted and 1.19% were severely wasted. The higher proportion of severe wasting was found in the Somali region, Harari region, among uneducated mothers, households with low income (poor and poorest), Muslim families and families with drink neither improved nor non-improved water. The results based on the proportional odds model indicate that there is a significant variation in wasting across community and household levels. The multilevel proportional odds model identified a child's sex, mother's education level, DBF, wealth index, antenatal care, source of drinking water and region of residence as significant risk covariates of wasting. We concluded that high prevalence of wasting is (over 7%) among children under five in Ethiopia, with concerningly high rates of severe wasting in specific groups. This suggests that interventions to address wasting in Ethiopia should be targeted towards these high-risk groups and consider both community-level and household-level risk covariates to reduce wasting among children in Ethiopia.

Key words: *Malnutrition, Wasting, and Multilevel.*

1. INTRODUCTION

1.1. Background of the study

Malnutrition refers to deficiencies or excesses in nutrient intake and imbalance of essential nutrients. The double burden of malnutrition consists of both undernutrition and overweight and obesity, as well as diet-related non-communicable diseases. Undernutrition manifests in four broad forms: wasting, stunting, underweight, and micronutrient deficiencies (WHO, 2021).

Wasting is defined as low weight-for-height. It often indicates recent severe weight loss, although it can also persist for a long time. It usually occurs when a person has not had food of adequate quality and quantity and/or they have had frequent or prolonged illnesses (WHO, 2021).

Wasting is a nutritional deficiency resulting from either inadequate energy or protein intake. Primary acute malnutrition is common in developing countries as a result of inadequate food supply caused by social, economic, and environmental factors (Dipasquale et al., 2020). Malnutrition, in all its forms, includes undernutrition (wasting, stunting, underweight), inadequate vitamins or minerals, overweight, obesity, and resulting diet-related non-communicable diseases (WHO, 2021).

According to (WHO, 2021), globally, 45 million children were estimated to be wasted (too thin for height), 1.9 billion adults are overweight or obese, while 462 million are underweight. Globally in 2020, 149 million under 5 children were estimated to be stunted (too short for age), and 38.9 million were overweight or obese. Around 45% of deaths among children under 5 years of age are linked to undernutrition. These mostly occur in low- and middle-income countries (Unicef, 2019; WHO, 2021). At the same time, in these same countries, rates of childhood overweight and obesity are rising (WHO, 2021). Child malnutrition was associated with 54% of deaths in children in developing countries in 2001 (WHO, 2013).

The global target for overweight among children under 5 years of age 28 in the African countries are on course to meet it, 20 countries are on course to reach the target exclusive breastfeeding among infants aged 0 to 5 months has, wasting among children under 5 years of age has 19 countries are course, while stunting among children under 5 years of age has six countries on course (GNR, 2022). However, not a single country in the region is on course to meet the targets for anaemia in women of reproductive age (aged 15 to 49 years), low birth weight, diabetes among men, diabetes among women, obesity among men, and obesity among women. 26 countries in the region have insufficient data to comprehensively assess their progress towards these global targets (GNR, 2022).

At least 216 million African children suffer from stunting and malnutrition. In sub-Saharan Africa, malnutrition is the second leading cause of death among children after malaria. To end this situation, the African Development Bank is stepping up actions and its calls for mobilization both in Africa and worldwide. In 2016, the Bank launched the African Leaders for Nutrition (ALN) initiative as an advocacy tool that would enable African countries to work with partners to boost nutrition on the continent (ADB, 2023).

Ethiopia has been blighted by malnutrition in recent years with an estimated 38% of children being stunted due to malnutrition. In Ethiopia, malnutrition is primarily due to a lack of sufficient consumption of 4 vitamins: Vitamin A, Zinc, iron, and iodine. This combined with a lack of sufficient calories per day has led to food poverty which plagues most of the country (Madduri, 2018). Undernutrition accounts for 45 percent of child mortality under the age of five, stunting still affects more than 5.4 million Ethiopian children under the age of five (39%) and, one in ten children under the age of five (about two million), and 45 percent of child deaths under age five are associated with undernutrition.

UNICEF works in partnership with the Government of Ethiopia to guarantee that disadvantaged children, pregnant women, and mothers have access to nutrition services and best feeding practices in both rural and urban settings, particularly during various emergencies (Unicef, 2019). In Ethiopia 28 percent of child deaths are associated with undernutrition, 38.6 percent of children under five are stunted, 21 percent of children under five are underweight. 7 percent of children under five suffer from wasting, 22% of women aged 15–49 years of age are undernourished, 58 percent of children are exclusively breastfed during the first 6 months and 14 percent of children aged 6–23 months are fed four or more food groups. 45 percent of children aged 6–23 are fed at least three times a day (Unicef, 2019).

1.2. Statement of the Problem

Wasting in children is associated with a higher risk of death if not treated properly (WHO, 2021). The developmental, economic, social, and medical impacts of the global burden of malnutrition are serious and lasting, for individuals and their families, for communities and for countries (WHO, 2013). Wasting is still one of the leading causes of morbidity and mortality in children under the age of five years worldwide (Robert et al, 2008). Severe acute malnutrition (SAM) or wasting is a life-threatening condition that affects millions of children under five years of age worldwide, especially in low- and middle-income countries (Joseph et al., 2023). Wasting is defined as a weight-for-height below -3 standard deviations of the median of the World Health Organization (WHO) growth standards, a mid-upper arm circumference (MUAC) below 115 mm, or the presence of bilateral oedema. Wasting increases, the risk of mortality, morbidity, and impaired growth and development in children. According to the 2019 Ethiopia Mini Demographic and Health Survey, the prevalence of SAM (wasting) among children aged 6-59 months was 7%, which translates to about 910,000 children suffering from SAM in the country(Ethiopian Public Health Institute (EPHI) & ICF, 2021). Wasting is a complex and multifactorial problem that is influenced by various individuals, households, and environmental factors. However, there is limited evidence about the determinants of SAM among children in Ethiopia, especially in the pastoral and agro-pastoral communities that are prone to food insecurity, drought, and conflict. Therefore, this study aims to identify the associated risk covariates of wasting among children aged under five in Ethiopia. Wasting has a higher impact on mortality than stunting, because wasting reflects acute malnutrition and severe weight loss, while stunting reflects chronic malnutrition and impaired growth (WHO, 2021). Wasting was responsible for 10.4% of all deaths in children under five, while stunting was responsible for 3.1%. (Robert et al, 2008) found that the case fatality rate of severe wasting was 21.9%, while that of severe stunting was 7.4%. Therefore, wasting may be more lethal than stunting. Since wasting is a killer it is considered as an outcome variable of the study.

1.3. Objectives of the study

1.3.1. General objective of the study

The overall aim of the study was to assess the risk covariates associated with wasting among children in Ethiopia.

1.3.2. Specific objectives

- ✓ To identify prevalence of wasting level in Ethiopia using 2019 EMDHS report data.
- ✓ To identify determinants of wasting using ordinal outcome variable.
- ✓ To identify if there is significance variation of children wasting among EA and household.

1.4. Significance of the study

The study would contribute to the existing knowledge about the risk covariates of wasting at different levels of analysis, such as individual, household, and community. The study could provide new insights and evidence on the multifaceted causes of wasting in Ethiopia. The study would use multilevel ordered regression, to account for the nested structure of the data and the ordinal nature of the outcome variable.

1.5. Limitation of the study

An ideal scenario for this study would have incorporated the most recent Ethiopia Demographic and Health Survey (DHS) data. However, due to unforeseen national circumstances, recent DHS is not available. This lack of current data presents a limitation, as the most recent findings might not fully capture the current situation regarding child malnutrition in Ethiopia. Utilizing the most up-to-date information would allow for a more precise understanding of the prevalence and risk factors associated with malnutrition, ultimately enabling the development of more targeted and effective interventions. In 2019 Ethiopian mini DHS data potential variables like the anaemic status of the child were not recorded, which may have a high contribution to waste.

1.6. Operational definitions

Severe acute malnutrition: results from insufficient energy (kilocalories), fat, protein, and/or other nutrients (vitamins and minerals, etc.) to cover individual needs(Gemechu et al., 2021; WHO, 2006).

Wasting: low weight-for-height. It often indicates recent and severe weight loss, although it can also persist for a long time (WHO, 2021).

2. LITERATURE REVIEW

2.1. Introduction

In this chapter, we will conduct a literature review on associated risk factors for under-five child malnutrition specially in wasting. Relevant papers are examined, with a particular emphasis on conclusions and methodological issues in developing nations.

2.2. Theoretical review

A review of the literature about the causes and consequences of child malnutrition in developing countries was done with a focus on the role of maternal education, health, and nutrition. The review also discusses the interventions and policies that have been implemented to address the problem of child malnutrition and their effectiveness (Brown et al., 2020).

The impact of climate change on child malnutrition was investigated in South Africa with a focus on the pathways and mechanisms through which climate variability and extremes affect food security, health, and nutrition outcomes. The review identifies the knowledge gaps and research priorities for improving the adaptation and resilience of vulnerable populations to climate change (Mkhize and Sibanda, 2020).

Determinants and measurements of child malnutrition in Pakistan were studied with a focus on the prevalence, trends, and regional disparities of stunting, wasting, and underweight among children under five years of age. The review examined data sources, methods, and challenges of assessing child malnutrition in Pakistan and provided recommendations for future research and policy (Rathnayake et al., 2020). Maternal factors and child malnutrition in Pakistan with a focus on the effects of maternal nutrition, health, education, empowerment, and care practices on child nutritional status was undertaken. The review explores the intergenerational transmission of malnutrition and the implications for policy and practice (Asim and Nawaz, 2018).

The nutrition status of children under the age of five years in South Africa was studied with a focus on socio-economic, demographic, environmental, and behavioral factors that influence child growth and development. The review evaluated the existing nutrition programs and interventions in South Africa and their impact on child nutrition outcomes (Juma et al., 2016).

2.3. Empirical review

A research done by (Chekol et al., 2022) in Ethiopia identified factors that were significantly associated with wasting. The findings show that maternal decision making on the use of household money (adjusted odd ratio (AOR)=3.04, 95% CI 1.08 to 7.83), complementary feeding started in a month (AOR=3.02, 95% CI 1.097 to 6.97), food diversity score (AOR=2.64, 95% CI 1.64 to 5.23), frequency of complementary feeding (AOR=6.68, 95% CI 3.6 to 11.25) and history of acute respiratory infections (ARIs) 2 weeks preceding the survey (AOR=3.21, 95% CI 1.07 to 7.86). Secondary data from EDHS, 2016, with a total of 7960 under-five children were used to explore the spatial distribution of malnutrition among under-five within and between the regions of Ethiopia (Kuse & Debeko, 2023). Among the under-five children included in the study, 36.6% were stunted, 12.2% were wasted and 25.2% were underweight. There was a significant spatial variation of malnutrition across the regions and Zones of Ethiopia. The significant source of spatial variation of malnutrition in children under five was associated with the mother's education level, drinking water facility, toilet facilities, number of children under-five in the household, household's wealth index, breastfeeding duration of the child, child size at birth, Body Mass Index of Mothers (BMI), region, and place of residence (Kuse & Debeko, 2023). A multivariate analysis was conducted in Kersa, Ethiopia to identify factors associated with WaSt, wasting, stunting and underweight. The prevalence of indicators of malnutrition was WaSt (5.8%), wasting (16.8%), stunting (53.9%) and underweight (36.9). Boys were more likely to be WaSt, wasted, stunted and underweight. Cough was associated with WaSt, wasting and underweight. Furthermore, maternal education, maternal occupation and maternal age were significantly associated with wasting (Roba et al., 2021).

Tesfaw (2008), carried out a research on Determinants of Nutritional status of children in Ethiopia using multileveled analysis showed that household economic status, mother's employment status, age of child, preceding birth interval and source of drinking water are factors that significantly affect nutritional status of children in Ethiopia.

Birhan and Belay (2021), used multilevel ordinal logistic regression model to identify associated risk covariates of underweight among under-five children in Ethiopia. They found that educational level of mother, religion, birth order, type of birth, sex of child, mother body mass index, birth size of child, existence of diarrhea and fever, duration of breast feeding, age of child and wealth index had significant effect on underweight among under-five children in Ethiopia.

Aheto (2020), employed simultaneous quantile regression to identify critical risk factors of under-five severe chronic malnutrition in Ghana. The study identified child level factors such as type of birth, sex, age, place of delivery and size at birth as well as maternal and household level factors such as maternal age and education, maternal national health insurance status, household wealth status, and number of children under-five in households as significant predictors of under-five severe chronic malnutrition.

Bi-variable and multivariable logistic regression models were used by Ahmed et al (2021) to examine the prevalence and associated factors of malaria among under-five children in Ethiopia. They found that family size, having more than two under-five children per household, presence and utilization of insecticide-treated net, outdoor stay at night, presence of stagnant water near to house, indoor residual spraying service, presence of hole on the wall of the house, and health information about malaria were significantly associated with malaria among under-five children in Ethiopia (Ahmed et al., 2021). A study conducted in the Kombolcha District of Eastern Hararghe Ethiopia identified child age, gender, immunisation status, antenatal care use, farm size, household size, water source, latrine use, and morbidity incidence as important factors for child malnutrition using multivariate logistic regression (Zewdie et al, 2013). A case-control study was undertaken to determine risk factors for severe acute malnutrition in children below 5 years of age in India by Mishra et al., (2014), the study showed that low birth weight, poor breastfeeding practices, delayed introduction of complementary feeding, inappropriate type and frequency of complementary feeding, recurrent infections, and low maternal education were significant risk factors for severe acute malnutrition in children.

Gebretsadik et al., (2023), carried out a multilevel mixed-effects linear regression to assess the prevalence and multi-level factors associated with acute malnutrition among under-five children in conflict-affected areas of Yemen. They found that household food insecurity, maternal undernutrition, lack of access to health services, and exposure to violence were significant predictors of acute malnutrition among under-five children in Yemen.

According to a research on the social and economic implications of child malnutrition in Ethiopia, more than two out of every five children are stunted. The yearly expenditures of child malnutrition are projected to be 55.5 billion ETB, which is 16.5% of the country's GDP. Elimination stunting in Ethiopia is a vital step towards growth and change (COHA, 2012).

A research was undertaken about prevalence and determinants of wasting of under-5 children in Bangladesh: Quantile regression approach by Hossain and Abdulla found that, the prevalence of wasting in children is about 8 percent and only approximately 1% percent of children were severely wasted in Bangladesh. Age, mother's BMI, and parental educational qualification, were all major factors of the WHZ score of a child (Hossain et al., 2022).

According to Gebremeskel et al, (2022) in Ethiopia, the prevalence of wasting among children under-5 years was 10.1% (901), of which 8.1% (632) had moderate wasting and 3.0% (269) had severe wasting. Children aged 36–47 months (AOR = 0.5; 95% CI: 0.4, 0.63), 48–59 (AOR = 0.5; 95% CI: 0.4–0.63), girls (AOR = 0.75; 95% CI: 0.65, 0.87), smaller-than-average birth weight (AOR = 1.94; 95% CI: 1.44, 2.61), very small birth weight (AOR = 1.75; 95% CI: 1.34, 2.30) were the individual-level factors associated with wasting, whereas husband's educational status (AOR = 0.37; 95% CI: 0.29, 0.69) was the household-level factor. Somalia (AOR = 1.72; 95% CI: 1.08, 2.74), Southern Nations Nationalities and People (SNNP) (AOR = 0.39; 95% CI: 0.24, 0.64), and Addis Ababa (AOR = 0.43; 95% CI: 0.21, 0.88) regions were the community-level factors associated with child wasting.

Getaneh et al (2019), used Bivariable and multivariable logistic regression models were fitted to identify associated factors of stunting and wasting in Ethiopia. A total of 523 school age children were with the median age of 12 (10–13 inter quartile range) years participated in the study. The overall prevalence of stunting and wasting among primary school children was 241(46.1%; 95% CI: 42.3, 50.3) and 47 (9%; 95% CI: 6.7, 11.7), respectively. Child age (AOR = 1.9, 95% CI: 1.29, 2.80), public tab/yard water source (AOR = 2.22; 95%CI: 1.46, 3.39), DDS < 4 (AOR = 1.89 95%CI: 1.08, 3.30), tea drinking habit (AOR = 0.46, 95%CI: 0.27, 0.80) and anaemia (AOR = 1.72 95%CI: 1.05, 2.83) were significant predictors of stunting. Moreover, child age (AOR = 3.91; 95% CI: 1.62, 9.44), maternal/care-givers' age ≤ 34 (AOR = 0.34; 95%CI: 0.16, 0.71), maternal education (AOR = 2.55; 95%CI: 1.15, 5.65), family poverty (AOR = 3.23; 95% CI: 1.30, 7.93) and alcohol consumption (AOR = 2.93; 95%CI: 1.16, 7.42) were found to be significantly associated with wasting.

According to Mulu et al. (2022) in northern Ethiopia the overall prevalence of stunting and wasting was 46.4% (95% CI: 41.6–51.5%) and 15.3 % (95% CI: 11.7–19.0%), respectively. They found that age (AOR = 0.18, 95% CI: 0.08, 0.47), substance use (AOR = 2.07, 95% CI: 1.33, 3.21), and loss of appetite (AOR = 2.00, 95% CI: 1.31, 3.04) were independently associated with stunting. Whereas age (AOR = 0.49, 95% CI: 0.27, 0.89), illness (AOR = 2.38, 95% CI: 1.27, 4.48), and open defecation (AOR = 2.27, 95% CI: 1.14, 4.51) were factors associated with wasting.

Dabale and Sharma (2014) used multilevel binary logistic regression to identify determinants of wasting among under-five children in Ethiopia; Found about 11.7 % of under-five children in Ethiopia were wasted. The results of study indicated that the risk of wasting was highest among male children, small size at birth, children whose parents resided in rural areas, children's of illiterate mothers, children whose mother's body mass index was low, children from poor families and children who had diarrhea and fever two weeks before the date of the survey. They also proved the existence of significant variations in the prevalence of wasting among the regions in Ethiopia.

According to a cross sectional analysis study on understanding child wasting in Ethiopia of 2019 EMDHS using generalized linear latent and mixed models, wasting was 7.68% (95% CI 6.56%-8.93%). Approximately 26.82% of women never sought prenatal treatment for their current kid. The majority of moms (52.2%) did not have a formal education, and 86.8% did not get postnatal care to their children. 50.93% of mothers had at least six household members. Wasting was associated with feeding diverse foods (coefficient 4.90, 95% CI 4.90-4.98), female sex of the household head (-40.40, 95% CI -40.41 to -40.32), home delivery (-35.51, 95% CI -35.55 to -35.47), first (16.66, 95% CI 16.60-16.72) and second (16.65, 95% CI 16.60-16.70) birth order, female child (-12.65, 95% CI -12.69 to -12.62), and household size of 1 to 3 (10.86, 95% CI 10.80-10.92) (Gilano et al., 2023).

2.3.1. Determinants of malnutrition east African countries

Kenya

A research done on determinant of under-five malnutrition in Kenya, employed logistic regression and found low age at birth longer duration of breast feeding low birth order low birth interval increased the likelihood of malnutrition of under five children in Kenya (Wainaina, 2019).

Masibo (2013) carried out a research on Trends and Determinants of Malnutrition among Children Age 0-59 Months. He obtained data from the Kenya Demographic and Health Surveys 1993, 1998, 2003, and 2008-09. It was found that the levels of stunting and underweight declined significantly over the study period, by 4.6 percentage points. Nonetheless, stunting remains of high public health significance in Kenya, while underweight is of medium public health significance, as per the World Health Organization (WHO) classification. Household wealth index, maternal education, maternal BMI, and size of the child at birth were significant determinants of child undernutrition.

A recent study by Mbogori and Muriuki (2021) about Demographic and Social-Economic Determinants of Malnutrition among Children (0-23 Months Old) in Kenya, found Wasting and stunting were significantly higher in children from rural areas, poorer wealth index, and mothers with no education. In contrast, children from urban areas, the richest wealth index category, and mothers with secondary or higher education were significantly more likely to be overweight or obese.

Hospital-based unmatched case control study in western Kenya employed unconditional logistic regression. A total of 94 cases and 281 controls were recruited. Of the cases, 84% (79/94) were under-nourished. Mother not having attended ante-natal clinic (OR = 7.9; 95% CI: 1.5–41.2), deworming (OR = 0.8; 95% CI: 0.4–1.2), and pre-lacteal feeding (OR = 1.8; 95% CI: 1.1–3.0) were associated with under-nutrition. Delayed developmental milestones (AOR = 13.9; 95% CI: 2.8–68.6); low birth weight (AOR = 3.3; 95% CI: 1.4–7.6), and paternal lack of formal education (AOR = 4.9; 95% CI: 1.3–18.9) were independently associated with under-nutrition (Gudu et al., 2020).

Jane et al (2008) showed that boys suffer more malnutrition than girls, and children of multiple births are more likely to be malnourished than singletons. The results further indicate that maternal education is a more important determinant of children's nutritional status than paternal education. Household assets are also important determinants of children's nutritional status.

Sudan

A study conducted to assess the prevalence of acute undernutrition after the COVID-19 pandemic and to identify the most important factors favouring the development of acute undernutrition found higher prevalence of acute gastroenteritis ($p < 0.05$) and parasitotic ($p < 0.05$). Infants aged 0–6 months were those with the lowest risk of undernutrition, whereas those aged 7–12 months were those with the greater risk (Chiopris et al., 2024).

A study by Jomah (2018) investigated on factors influencing malnutrition in children under five in Sudan. Their findings highlighted several key areas. First, proper breastfeeding practices were identified as crucial. Second, maintaining good hygiene around the child was important. Third, ensuring the child receives additional nutritious foods beyond breastmilk at the appropriate time was another factor. Finally, the study found that good sanitation and care practices, along with maternal health and nutrition, all played significant roles in reducing malnutrition in young children.

A research done by (Tanyi, 2007) found that 18 percent of children between 6-59 months of age had wasting. Maternal education, main source of water, and income were strongly related to wasting. Gender of head of household was not found to have a significant relationship with wasting. Mothers with at least primary education were much less likely to have malnourished children, even after controlling for income and environmental conditions. Children in households with unsafe sources of water were 2.6 more likely to have wasting than those with piped in/tube wells as their main source of water. For every increase of 100 dinars in a household, the children in the household are approximately two-thirds times (0.662) less likely to be wasted.

Abu-Fatima et al. (2020) showed that diseases associated with undernutrition in children include higher risk of anaemia, diarrhea, and respiratory infections. The study estimated that these additional cases of illness are costly to the health system and families (63% and 37%, respectively). Undernourished children are also at higher risk of dying, and 37.7% of all child mortality cases in Sudan are associated with undernutrition.

Northern of Ethiopia

Kelati et al. (2014) studied the prevalence of acute malnutrition and associated factors among children aged 6-59 months in mai-Aini Eritrean Refugees' Camp, Northern Ethiopia. The results showed that 33.4% and 24.6% of children were underweight and wasted, respectively. Prevalence of acute malnutrition was higher in males compared to females. Underweight was associated with child age, consuming extra food during pregnancy and maternal BMI less than 18.5 Kg/m2. Children age and receiving pre-lactate food was independently associated with wasting.

A multivariable multilevel logistic regression was employed in a study aimed at identifying individual and community level factors associated with acute malnutrition among children aged 6–59 months from armed conflict affected settings of Tigray, Ethiopia. Individual-level factors such as older child age (AOR = 0.13, 95% CI: 0.10, 0.18), female child sex (AOR = 1.24, 95% CI 1.05, 1.480.95), Vitamin-A supplement (AOR = 1.3, 95% CI: 1.05, 1.65), and history of diarrhea (AOR = 1.22, 95%CI: 1.02, 1.53) and community-level factors like unimproved drinking water source (AOR = 1.31, 95%CI: 1.08, 1.58), unimproved toilet facility (AOR = 1.24, 95% CI: 1.01, 1.52), and severe food insecurity (AOR = 1.55, 95% CI: 1.16. 2.07) were significantly associated with childhood acute malnutrition (Gebretsadik et al., 2023b).

Somalia

Donkor et al. (2022) researched risk factors of stunting and wasting in Somali pre-school age children: based on results from the 2019 Somalia micronutrient survey. They employed Bivariate and multivariable analyses separately for children 0–5 months and 6–59 months, and population attributable fractions were calculated using adjusted risk ratios produced by Poisson regression models. The result showed that household wealth, with the risk of wasting increased significantly as the household wealth quintile decreased. Among children 0–5 months of age no variables remained statistically significantly associated with stunting in the multivariable analysis.

Mohamoud Ali et al. (2022)showed that the prevalence of children stunted was higher among children born to mothers without ANC visits in Somalia. Children from households who use traditional fuel types (firewood and charcoal) are more likely to be undernourished and children aged 6 to 11 months, children aged 12 to 17 months, and those aged 24 to 59 months had the highest odds of being stunted, as they are 1.58, 2.12, and 165 times more likely to be stunted respectively compared to children aged 0-5 months.

Gebremichael & Gebretsadik (2022), carried out a research on the prevalence of wasting and associated factors among children aged 6-23 months in Garowe, Puntland. The results showed the prevalence of wasting among children aged 6-23 months was 34.2%, (95%CI 28.7 CI, 40.3); of which, 12% were severely wasted. Being from daily laborer father (AOR=3.1, 95% CI: (1.1, 8.7)), initiating complementary feeding before six months (AOR=8, 95% CI: (4.5, 14)) , breastfeeding initiation after some hour of birth (AOR=3.9, 95% CI: (1.8, 8.4)), being unvaccinated (AOR=2.9, 95% CI:(1.7, 5.2)), mother with no formal education (AOR=3.4, 95% CI: (1.6, 7.0)) and mothers who didn't attend ANC follow-up during last pregnancy (AOR=5.3, 95% CI: (2.9, 9.5) were significantly associated with occurrence of wasting among children aged 6-23 months.

Djibouti

A master's thesis by (Aden, 2010) studied the status of malnutrition among children aged 0-5 years in Djibouti. The result indicates 17 potential risk factors contributing to malnutrition six of them are statistically significant risks including difficulty accessing a health care center (OR=2.61), low education among parents (mother, OR=2.58; father, OR=1.73), practice of traditional medicine (anal scratching, OR=1.42), lack of good nutrition (meat, OR=1.85), and child anaemia (OR=1.76).

2.4. Conceptual framework

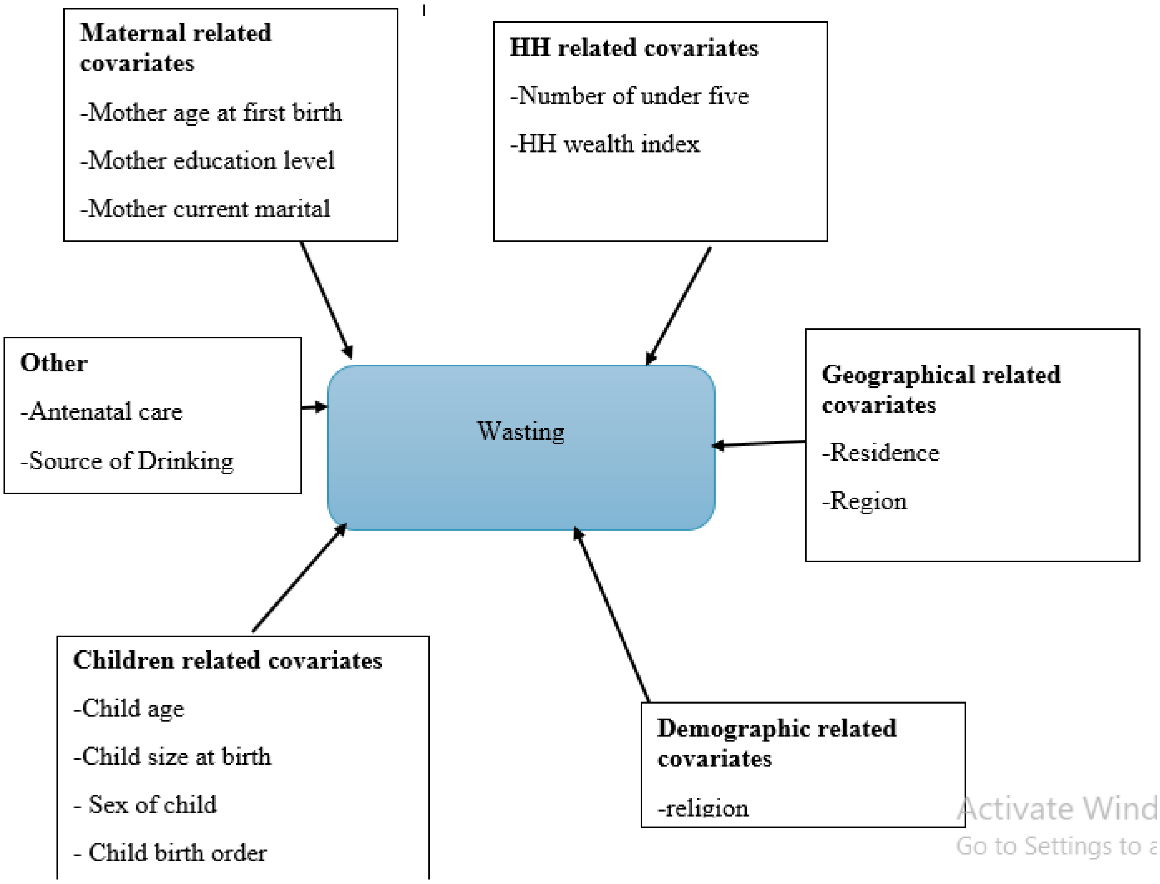

Figure 1: Conceptual frame work

Source: our review 2024

3. DATA AND METHODOLOGY

3.1. Introduction

In this chapter, we describe the data and methodology that were used to address the objectives of our study. The data source is the Ethiopian Mini Demographic and Health Survey (EMDHS) conducted in 2019. The variables that we used in our analysis include the outcome variable, which is the nutritional status of children measured by WHZ, and the explanatory variables are presented in Table 1 below. The methodology that was employed to model the multilevel ordered logistic regression was introduced. The assumptions, estimation methods and variable selection criteria will be presented.

3.2. Description of the study area

Ethiopia, located in the Horn of Africa, is the second-most populous country in Africa with an estimated population of 107.33 million as of 2023. The country is ethnically diverse, with over 80 different ethnic groups, the largest being the Oromo (34.4%) and Amhara (27.0%) (CSA, 2023).

Despite recent economic growth, Ethiopia continues to face significant development challenges. The country ranks near the bottom on the Human Development Index, with Sudan at 168th and South Sudan at 189th out of 189 countries. Poverty, weak infrastructure, frequent droughts, and limited livelihood opportunities are major issues. In terms of health, Ethiopia has made progress in improving life expectancy, which was reported to be 56 years for males and 60 years for females in 2013. However, the country still faces challenges in providing adequate healthcare access, especially in rural areas. Education is another area of concern. While Ethiopia has expanded access to primary education, quality and retention remain issues, particularly for girls. The country's literacy rate was estimated at 51.8% in 2017. To address these challenges, Ethiopia will need to continue investing in infrastructure, healthcare, and education, while also promoting sustainable economic development and good governance. International cooperation and support will be crucial in helping Ethiopia achieve its development goals

3.3. Data source

The data for this study were taken from EMDHS 2019. The 2019 Ethiopian Mini Demographic and Health Survey (EMDHS), conducted by the Ethiopian Public Health Institute (EPHI) in collaboration with various agencies, aimed to update key demographic and health indicators. The survey, aligned with the Sustainable Development Goals, was carried out from March 21 to June 28, 2019, using a two-stage stratified sample of 305 enumeration areas (EAs) from the 2019 Ethiopia Population and Housing Census. The sample design provided estimates for the entire country, urban and rural areas, and all regions. Data collection included interviews with women aged 15-49 and measurements of children under five, revealing that 38% were stunted, 24% underweight, and 7% wasted, indicating prevalent malnutrition (EPHI & ICF, 2021). The data were accessible from the DHS program website after authorization.

3.4. Study population

The study population is all the under-five children residents of Ethiopia using the 2019 EMDHS data set. From the 5,189 under-five children in the 2019 EMDHS, the current study on the wasting level of children is based on 5,164 under-five children with complete anthropometric measurements. The study considered the weight-for-height anthropometric index as an indicator of a child's wasting status.

3.5. Study design

The study design for this research was a cross-sectional survey conducted in 2019 using a population-based representative sample, ensuring a broad and inclusive representation of the target population.

3.6. Sampling techniques

The 2019 EMDHS sample was selected using a stratified (rural and urban from each region city administration) and clustered and selected in two stages. In the EMDHS 2019 a representative sample of approximately 9150 households from 305 clusters was selected. The sample was selected in two stages. In the first stage, 305 Enumeration Areas were selected. In the second stage, a fixed number of 30 households were selected for each enumeration area. Among the 305 selected Enumeration Areas, 93 are in urban areas and 212 are in rural areas.

3.7. Study variables

3.7.1. The response variable

The response variable in this study was the wasting level of children. Wasting is a form of acute malnutrition that occurs when a child’s weight is too low for their height. Wasting can be classified into three categories based on the child’s weight-for-height z-score (WHZ), which is a measure of how many standard deviations a child’s weight is from the median weight of a healthy child of the same height. Severely wasted children are at a very high risk of death and need urgent treatment with ready-to-use therapeutic food and medical care. Moderately wasted children are also at an increased risk of death and need treatment with ready-to-use supplementary food and medical care. Normal wasted children mean that the child's weight is within the normal range for their height and weight, according to the WHO Child Growth Standards (WHO, 2006).

$$Yijk = \begin{cases} Severely\ wasted & if, \quad WHZ < -3\,SD \\ moderately\ wasted & if, \quad -3\,SD \le WHZ < -2\,SD \\ Normal & if, \quad WHZ \ge -2\ SD \end{cases}$$

where i is i^{th} children from j^{th} HH and k^{th} EA.

3.7.2. Predictor variables

A number of explanatory variables at the individual (child), family, demographic, socio economic and geographical covariates are expected to be associated with child wasting, these include region, urban/rural residence, sex, child age in months, birth order, household wealth index, number of children under five age in a HH, and DBF, religion, mother's age at first childbirth, mother's present marital status, source of drinking water, antenatal care and mother's level of education.

Table 1: Description of the predictor variables

Variable name	Description	Categories
Sex_of_child	Sex of child	(1) Male (2) Female
Region	Region of the child	(1) Tigray (2) Afar (3) Amhara (4) Oromia (5) Somali (6) Benishangul (7) SNNP (8) Gambella (9) Harari (10) Addis Ababa (11) Dire Dawa
Residence	Type of place of residence	(1) Urban

		(2) Rural
Wealth index	Socio economic status of family	(1) Low income (2) Middle income (3) High income
Mother_Edu1	Mother Education level	(1) Illiterate (2) Primary (3) Secondary and above
Marital_Status1	Mother's present marital status	(1) Unmarried (2) Married (3) Widowed (4) Divorced
mother_age_at	Mother's age at first childbirth	(1) 10-20 (2) 21-30 (3) Above 30
Religion	Religion of child household head	(1) Orthodox (2) Protestant (3) Muslim (4) Other
Birth_O	Birth order of the child	(1)1-5 (2) 6-10 (3)Above 10
DBF	Duration of breast feeding	(1) Ever breasted (2) Never breasted (3) Still breasting
Child_age	Child age in months	(1) 0-12 months (2) 13-24 months (3) 25-36 months (4) 37-48 months (5) 49-59 months
Underfive	Number of under-five children in the household	(1) <3 (2) 3 and above

Antenatal_c	During pregnancy, given or bought iron tablets	(0) No (1) Yes
Source_dw	Source of drinking water	(1) Non improved, (2) Improved (3) Other

3.8. Methods of data analysis

3.8.1. Descriptive analysis

Descriptive statistical analyses, including weighted frequency tables and percentages, were employed to provide a comprehensive and easily understandable overview of the data. These analytical techniques allowed for the clear and concise presentation of the study findings, enabling readers to grasp the key results at a glance while also providing a more detailed breakdown of the data when needed.

3.8.2. Ordinal logistic regression model

The ordinal logistic regression procedure empowers one to select the predictive model for ordered dependent variables. It describes the relationship between an ordered response variable and a set of explanatory variables. The explanatory variables may be continuous or discrete or any type (Agresti, 2002). There are several ordinal logistic regression models such as the proportional odds model (POM), two versions of the partial proportional odds model without restrictions and with restrictions, the continuous ratio model, and the stereotype model. The most popular model in ordinal logistics is the Proportional Odds model. In this particular study, the logit link function with POM was used (Hosmer and Lemeshow, 2000).

3.8.3. Proportional odds model (POM)

The proportional odds model assumes the effect of each covariate in X is the same across the $C-1$ cumulative logits (Hedeker, 2015). Tests of the proportional odds assumption can then be performed by comparing models: (a) assuming proportional odds vs. (b) relaxing proportional odds assumption. Comparing the model deviances that are obtained from these two analyses provides a likelihood ratio test of the proportional odds assumption for the set of covariates under consideration (Hedeker, 2015). Hence the proportional odds assumption is not violated, proportional odds model was employed. When response categories are ordered logit can directly incorporate the ordering. Define i^{th} cumulative probability that the response Y falls in category i or below as

$$P((\mathrm{Y} \leq \mathrm{i}) = \pi_i,\ \mathrm{i} = 1, \ldots \ldots .. \mathrm{c}\ \text{-}1 \tag{3.1}$$

And

$$P(\mathrm{Y} \leq 1) \leq \mathrm{P}(\mathrm{Y} \leq 2) \leq \ldots \ldots \ldots \leq \mathrm{P}(\mathrm{Y} \leq \mathrm{i}) = 1 \qquad , \mathrm{i}= 1, 2..., \mathrm{c} \tag{3.2}$$

Models for cumulative probabilities do not use the final one P(Y≤ i), since it equals 1, takes categorical response variable with c ordered categories, the cumulative probability of the first c-1 of $Y\ is\ P\ (Y \leq\ i)\ = \pi_i, i\ =\ 1, \ldots, c\ -\ 1$. then, the odds ratio of the first c-1 cumulative are

$$Odds\ (pr(Y \leq i)) = \log[\frac{P(Y\leq i)}{1-P(Y\leq i)}] \qquad \mathrm{i}= 1, 2, \ldots, \mathrm{c}\text{-}1 \tag{3.3}$$

Consider a collection of P predictor variables denoted by the vector $X' = (X1, X2, X3, \ldots \ldots XP)$. The relationship between the predictor and response variables is not a linear function in logistic regression; instead, the logistic regression function is used, which is the logit transformation of π.

$$\pi_{\mathrm{i}} = \frac{\exp(\alpha_i+\beta_1 X_1+\cdots+\beta_p X_p)}{1+\exp(\alpha_i+\beta_1 X_1+\cdots+\beta_p X_p)} \tag{3.4}$$

Then the logit or log-odds of having $P(\ Y \leq i\ ) = \pi_i$ is modeled as a linear function of the explanatory variables as

$$\log\left[\frac{P(Y\leq i)}{1-P(Y\leq i)}\right] = \log\left[\frac{\pi_i}{1-\pi_i}\right] = \ \alpha_i + \beta_1 X_1 + \cdots + \beta_p X_p \tag{3.5}$$

Equivalent with

$$\log\left[\frac{\pi_i}{1-\pi_i}\right] = \ \alpha_i\ +\ \sum_{j=1}^{p} \beta_p X_p,\ i =\ 1, \ldots\ , c -\ 1\ and\ j\ =\ 1, \ldots\ , p \tag{3.6}$$

Where: α_i = threshold value, β_j= parameter and X_j= sets of factors or predictors. The model assumes a linear relationship for each logit and parallel regression lines. The above equation is called the proportional odds model and it estimates simultaneously multiple equations of cumulative probability. An equation is solved for each category of the dependent variable except the last one. In this model, each logit has its term called the threshold value and their values do not depend on the values of the independent variable for a particular case.

3.8.3.1. Testing of parallel lines

To test the parallel assumption in ordinal logistic regression models, the Brant test is commonly used. The parallel regression assumption, also known as the proportional odds assumption, states that the relationship between each pair of outcome groups is the same. In other words, the coefficients that describe the relationship between the lowest outcome category and all higher categories are the same as those that describe the relationship between the next lowest category and all higher categories, and so on. The Brant test, developed by Brant (1990), assesses whether the parallel regression assumption holds for an ordinal logistic regression model. It compares the coefficients from the ordinal logistic regression model to those from a series of binary logistic regression models. If the parallel regression assumption is met, the coefficients should be similar across the binary logistic regressions. The Brant test generates a chi-square statistic and a p-value. A significant p-value (typically less than 0.05) suggests that the parallel regression assumption is violated, indicating that the ordinal logistic regression model may not be appropriate. In such cases, alternative models, such as the generalized ordered logit model or the partial proportional odds model, can be considered.

3.8.4. Odds ratio

First let's establish some notation and review the concepts involved in ordinal logistic regression. Let Y be an ordinal outcome with C categories. Then $P(Y \le i)$ is the cumulative probability of Y less than or equal to a specific category $i = 1, \cdots, C-1$. Note that $P(Y \le i) =$ 1 (Bruin, 2011).The odds of being less than or equal a particular category can be defined as

$$\frac{P(Y\le i)}{P(Y>i)} \tag{3.7}$$

for $i = 1, \cdots, C-1$ since $P(Y > i) = 0$ and dividing by zero is undefined. Alternatively, you can write $P(Y > i) = 1 – P(Y \le i)$.The log odds is also known as the logit, so that

$$log\frac{P(Y \le i)}{P(Y > i)} = logit\big(P(Y \le i)\big) \tag{3.8}$$

The ordinal logistic regression model can be defined as

$$logit\big(P(Y \le i)\big) = \beta_{i0} + \beta_{i1}x_1 + \cdots + \beta_{ip}x_p, \tag{3.9}$$

where $\beta_{i0}, \beta_{i1}, \cdots + \beta_{ip}$ are model coefficient parameters (i.e., intercept and slopes) with p predictors for i= $1, \cdots, C-1$. Due to the parallel lines assumption, the intercepts are different for each category but the slopes are constant across categories, which simplifies the equation above to (Bruin, 2011).

$$logit(P(Y \leq i)) = \beta_{i0} + \beta_1 x_1 + \cdots + \beta_p x_p. \tag{3.10}$$

3.8.5. Variables and model selection criteria

In this study Akaike information criterion and the Bayesian information criterion were used to balance the fit and complexity of the model.

$$AIC = -2\ln(l(model)) + 2k \tag{3.11}$$

Where: k is number of estimated parameters, L (model) is the likelihood of the model

$$BIC = 2\ln(L(model)) + k\log(n) \tag{3.12}$$

Where: k is a number of estimated parameters L (model) is the likelihood of the model, n is a number of observations. Based on the model selection criterion stated above the model with the smallest AIC and BIC value could be considered a better fit model.

3.8.6. Goodness-of-fit tests

The likelihood-ratio test is a powerful and widely used method for comparing null models and assessing the statistical significance of model parameters. It provides an intuitive way to quantify the evidence in favor of one model over another based on the relative likelihoods of the two models given the observed data (Hosmer and Lemeshow, 2000). If the test statistic is greater than the critical value from the chi-square distribution, the null hypothesis is rejected, indicating that the alternative model provides a significantly better fit to the data. The study used tests like the likelihood ratio test.

$$G^2 = -2(\ln(lo - l1)) \tag{3.13}$$

Where l_o is the likelihood of the null model and l_1 is the likelihood of the saturated model. If the p-value for the overall model fit statistic is less than the conventional 0.05, the null hypothesis is rejected and we conclude that there is evidence that at least one of the independent variables contributes to the prediction of the outcome (Hosmer and Lemeshow, 2000).

3.8.7. Model adequacy checking

After fitting a model, the primary stage in regression analysis is to ensure its appropriateness. It can be measures based on diagnosing residuals and measures of influence.

3.8.7.1. Residuals

Residuals are the difference between the observed and predicted values of the response variable. Residuals are useful in identifying observations that are not explained well by the model. For logistic regression diagnostics, the residuals are calculated in a similar way as usual. Plot the residuals (such as Pearson, deviance, standardized, or surrogate residuals) against the predicted probabilities values, the covariates to examine the patterns and trends (Snijders and Berkhof, 2008).

Let Y_i denote the binomial variate for n_i trials at setting i of the explanatory variables, i=1, 2…N. Let $\hat{\pi}_i$ denote the model estimate of P(Y=1). Then $n_i\hat{\pi}_i$is the fitted number of successes.

The person residual is defined as:

$$e_i = \frac{(Y_i - \widehat{N\pi}_i)}{\sqrt{Var((Y_i)}} \tag{3.14}$$

With $\hat{\pi}_i$ replaced by π_i in the numerator of the Pearson residual, is the difference between a binomial random variable and its expectation, divided by its estimated standard deviation; for large n≥ 30, has an approximate N (0, 1) distribution. Since π_i is estimated by $\hat{\pi}_i$ and $\hat{\pi}_i$ depends on Yi, The Pearson residuals do not have unit variance since no allowance has been made for the inherent variation in the fitted value. A better procedure is to further adjust the Pearson residuals by their estimated standard deviation that contains variation due to the effect leverage value this adjustment gives Pearson residual.

Deviance residuals are used to check for lack of fit by considering the i^{th} observation. Logistic regression is a type of generalized linear model. If the model fits poorly based on the overall goodness-of-fit test, examination of residuals highlights where the fit is poor. This residual uses the components of the deviance statistic. The deviance residual for observation i is defined as:

$$\sqrt{d_i}\ X(sign(Y_i - n_i\hat{\pi}_i)) \tag{3.15}$$

Where $d_i = 2(Y_i \log\left(\frac{Y_i}{n_i\hat{\pi}_i}\right) + (n_i - Y_i)\log(n_i - Y_i)\,/(n_i - n_i\hat{\pi}_i)$ (3.16)

DFBETA(S): is a diagnostic measure which measures the change in the logit coefficients for a given variable when a case is dropped. If DFBETA(S) is less than unity, this implies no specific impact of an observation on the coefficient of a particular predictor variable, while DFBETA of a case greater than 1.0 implies that the observation is outlier (Robinson et al., 1984).

3.9. Multilevel model

Psychologists, as well as researchers in allied fields of health, education, and social sciences, are often in the position of collecting and analysing nested (clustered) data. Two frequently encountered types of nested data are hierarchically clustered observations, such as individuals nested within groups, and longitudinal data, or repeated measures over time. Both data structures share a common feature: dependence of observations within units (observations) within clusters or repeated measures within persons). Because classical statistical models like analysis of variance and linear regression assume independence, alternative statistical models are required to analyze nested data appropriately (Bauer and Sterba, 2011). Typically, different surveys contain multiple levels of nesting. When analysing such datasets, a multilevel model is generally more appropriate than an ordinary single-level regression model because it enables one to deal with the hierarchical structure of variables (Snijders and Berkhof, 2008). Multilevel modelling allows researchers to estimate the effects of fixed and random variables simultaneously (Silvia, 2007).

3.9.1. Multilevel Generalized Linear Models for Ordinal Outcome

Multilevel generalized linear models for ordinal outcome are statistical models that can handle ordinal response variables that are measured repeatedly or clustered within groups. These models can account for the correlation among observations from the same group or subject, and also allow for covariates that may affect the outcome.

In this study the nature of data indicate that dependence in the group within enumeration area(EA) and HH. To handle this dependency multilevel is appropriate statistical method(De Silva et al, 2012). Using ordered outcomes yields more parsimoniously parameterized models. A common tool for analyzing regression data with ordinal responses is the POM. The model assumes that the response variable Y_{ijk}, here wasting level for subject i in j HH and cluster j. The cumulative probabilities for multilevel model is given by:

$$logit(P(Y_{ijk} < i \mid X_{ijk})) = \beta_{oc} + X'\beta + u_j + v_k \qquad (3.17)$$

u_j *and* v_k *represents household and Cluster effect respectively.*

where u_j and v_k ~ N(0; σ^2). The weighted multilevel analysis was done using Stata software version 18 and R.

3.9.2. Parameter Estimation for Multilevel Logistic Regression Model

In this study ML estimation method was employed to estimate the parameters of all models.

3.9.3. Intercept only model

This model is the simplest model which predicts the outcome based solely on the overall mean of the data. It does not include any predictors or random effects. The equation for an ordinal outcome would be similar to a logistic regression but without any predictors.

$$P(Y \leq j) = \frac{\exp(\alpha_j)}{1 + \exp(\alpha_j)} \tag{3.18}$$

where ($P(Y \leq j)$) is the probability of the ordinal outcome being less than or equal to a certain category (j), and (α_j) is the intercept for category (j).

3.9.4. Random Intercept Model

This model allows for random variation at the subject or group level. It includes a random intercept that accounts for the variability between subjects or groups. The equation for an ordinal outcome can be expressed as

$$logit\left(P\left(Y_{ijk} \leq i\right)\right) = \alpha_{jki} + X'\beta + u_j + v_k \tag{3.19}$$

where Y_{ijk} is the response for the i^{th} observation in the j^{th} HH, (k) EA, c is the category level, α_{ijc} is the fixed intercept for the j^{th} and k^{th} groups and c^{th} category, u_j *and* v_k are the random effect for the j^{th} HH and k^{th} EA.

3.9.5. Random Coefficient Model

This model extends the random intercept model by allowing the slopes of the predictors to vary across subjects or groups. In addition to the random intercept, each predictor has a random slope associated with it. The general form of the equation for an ordinal outcome is

$$logit\left(P\left(Y_{ijk} \leq i\right)\right) = \alpha_{jki} + \sum_{p=1}^{P} (\beta_p + u_{jp} + v_{kp})X_{ijkp} \tag{3.20}$$

where β_p is the fixed effect of the p^th^ predictor, u_{jp} and $v_{kp}$is the random effect associated with the p^th^ predictor in the j^th^ and k^th^ groups, and X_{ijkp} is the value of the p^th^ predictor for the i^th^ observation in the the j^th^ and k^th^ groups.

When selecting the best-fitting model for multilevel ordinal logistic regression, it's crucial to consider both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) as measures of model quality. The Intercept Only Model serves as a baseline, providing a simple mean-based prediction without predictors. The Random Intercept Model introduces variability at the group level, accommodating differences between subjects. The Random Coefficient Model further refines this by allowing predictor slopes to vary across groups. By comparing the AIC and BIC values, which penalize model complexity to prevent overfitting, we can determine the most appropriate model. Lower AIC and BIC values indicate a better balance between model fit and complexity, guiding us towards the model that most accurately captures the underlying patterns in the data while remaining parsimonious.

3.9.6. Intra-class Correlation (ICC)

For a multilevel model, it is often of interest to express the cluster variance in terms of an intra class correlation (ICC). The ICC indicates correlation between observation in same groups (EA and HH), and is given by:

$$ICC_{household} = \frac{\sigma^2 j}{\sigma^2 j + \sigma^2} \tag{3.21}$$

$$ICC_{EA} = \frac{\sigma^2 k}{\sigma^2 k + \sigma^2} \tag{3.22}$$

$$ICC_{total} = \frac{\sigma^2 j + \sigma^2 k}{\sigma^2 j + \sigma^2 k + \sigma^2} \tag{3.23}$$

Where $\sigma^2\mathbf{j}$ is the cluster or level 3 (EA) variance, $\sigma^2 k$ is the level 2 (household) variance and σ^2 is level 1 variation of individual. For a logistic regression model (either binary or ordinal), the level-1 variance, which is not estimated, equals the variance of the standard logistic distribution $\frac{\boldsymbol{\pi}^2}{\mathbf{3}} = 3.29$ (Evans et al, 1993).

3.9.6.1. Testing the significance of random effects

We tested hypotheses at a 5% level of significance to determine the inclusion of specific random effects. Ho: the variance of the random effects is equal to zero Versus Ha: the random effect variance is greater than zero. Depending on p- value, of likelihood ratio test we reject H_o if p-value is less than 0.05 and conclude that the random effects is significant.

4. RESULTS

4.1. Wasting level of children in Ethiopia

Table 2 vividly illustrates the state of child wasting prevalence in Ethiopia. Out of 5029 children, the majority 92.76%(4665) is categorized as under normal wasting levels. This is a heartening statistic, reflecting the effectiveness of current health and nutrition programs aimed at ensuring the well-being of the young population. 6.06%(304) of children are experiencing moderate wasting. These children are likely in need of supplementary feeding programs and nutritional support to restore their health to an optimal level. The most alarming figure, however, is the 1.19% (60) representing children with severe wasting. This critical condition is indicative of acute malnutrition and requires immediate medical intervention. Children in this category are extremely underweight for their height, and their immune systems are likely compromised, making them highly susceptible to infections and diseases.

Table 2: Prevalence of wasting level

<table>
<tr><th>Wasting level</th><th>frequency</th><th colspan="2">percent</th></tr>
<tr><td>Normal</td><td>4665</td><td colspan="2">92.76</td></tr>
<tr><td>Moderately wasted</td><td>304</td><td>6.06</td><td rowspan="2">Total 7.25% are wasted</td></tr>
<tr><td>Severely wasted</td><td>60</td><td>1.19</td></tr>
<tr><td>Total</td><td>5029</td><td colspan="2">100</td></tr>
</table>

Source; Ethiopia 2019 mini DHS data.

4.2. Description of variables

The data from the mini 2019 DHS survey in Ethiopia reveal some striking percentages that highlight the disparities in child nutrition, particularly in terms of wasting level among children under five years. Among male children 91.02% of male children were normal, 7.37% moderately wasted and 1.61% severely wasted. Among female children show a higher normal rate at 94.55% were normal, with 4.70% moderately wasted and 0.75% severely wasted. By region, Oromia records the highest normal rate at 95.55%, while Somali has the highest severe wasting at 6.04%. Urban residence is associated with a 94.28% normal rate, slightly higher than the rural rate of 92.25%. Low-income families have a 90.33% normal rate, with higher rates of moderate and severe wasting compared to middle and high-income groups. Children of illiterate mothers have a 90.65% normal rate, with higher wasting rates than those whose mothers have primary or higher education levels. Unmarried mothers have a 99.26% normal rate, but this is based on a very small sample size. Mothers who had their first child between the ages of 10-20 have a 92.54% normal rate, while those above 30 have a 98.48% normal rate. Among religions, Protestant children have a 95.41% normal rate, and Harari has the highest severe wasting at 17.0%. First to fifth-born children have a 93.05% normal rate, which is higher than those above the tenth order. Children who were ever breastfed have a 92.92% normal rate. Households with fewer than three under-five children show a 93.27% normal rate. The age of the child in months indicates that those aged 37-48 months have a 95.0% normal rate. Improved drinking water sources are associated with a 92% normal rate, and antenatal care shows a 91.36% normal rate for those who received it, compared to 94.5% for those who did not (for details see Table 3).

Table 3: Description statistics of variables

		Level of wasting		
Predictors	Categories	Normal	Moderately wasted	Severely wasted
Sex of child	Male	2329 (91.02%)	189 (7.37%)	41 (1.61%)
	Female	2336 (94.55%)	115 (4.70%)	19(0.75%)
	Total	4665(92.6%)	304(6.06%)	60 (1.19%)
Region	Tigray	320 (90.97%)	29 (8.30%)	3 (0.85%)
	Afar	66 (85.8%)	8 (11.27%)	2 (2.6%)
	Amhara	890 (92.36%)	58 (6.0%)	16 (1.67%)
	Oromia	1907 (95.55%)	84 (4.21%)	5 (0.25%)
	Somali	273 (78.76%)	52 (15.2%)	21 (6.04%)
	Benishangul	56 (94.01%)	3 (5.51%)	1(1.67%)
	SNNPR	960 (93.71%)	56 (5.49 %)	8 (0.8%)
	Gambela	19 (87.2%)	2 (9.98%)	1 (2.82%)
	Harari	14 (80.0%)	1 (3.0%)	3 (17.0%)
	Addis Ababa	135 (93.15%)	9 (6.20%)	1 (0.68%)
	Dire Dawa	24 (88.88%)	2 (7.40%)	1 (3.70%)
	Total	4665(92.6%)	304(6.06%)	60 (1.19%)
Residence	Urban	1182 (94.28%)	58 (6.64%)	14 (1.1%)
	Rural	3483 (92.25%)	246 (6.53 %)	46 (1.22%)
	Total	4665(92.6%)	304(6.06%)	60 (1.19%)
	Low income	2064 (90.33%)	178 (7.80%)	43 (2.0%)

Wealth	Middle income	889 (94.91%)	42 (4.55%)	5 (0.54%)
	High income	1712 (94.70%)	84 (4.7%)	12 (0.67%)
	Total	4665(92.6%)	304(6.06%)	60 (1.19%)
Mother's highest education level	Illiterate	2458 (90.65%)	207 (7.64%)	47 (1.8%)
	Primary	1682 (95.05%)	76 (4.32%)	11 (0.63%)
	Secondary and above	225 (95.77%)	21 (3.84 %)	2 (0.39%)
	Total	4665(92.6%)	304(6.06%)	60 (1.19%)
Mother's present marital status	Unmarried	17 (99.26%)	1 (5.0%)	1 (5.0%)
	Married	4434 (92.79%)	285 (5.98%)	58 (1.23%)
	Widowed	54 (93.48%)	4 (6.46%)	1 (1.85%)
	Divorced	158 (90.83%)	15 (8.61%)	1 (0.57%)
	Total	4665(92.6%)	304(6.06%)	60 (1.19%)
Mother's age at first child birth	10-20	3340 (92.54%)	215 (6.0%)	53 (1.48 %)
	21-30	1263 (93.05%)	88 (6.50%)	6 (0.45%)
	>30	61 (98.48%)	1 (1.58%)	1 (1.58%)
	Total	4665(92.6%)	304(6.06%)	60 (1.19%)
Religion	Orthodox	1579 (92.0%)	116(6.75%)	21 (1.26%)
	Protestant	1307 (95.41%)	61 (4.45%)	2 (0.2%)
	Muslim	1692 (91.79%)	116 (6.30%)	35 (1.91%)
	Other	86 (87.31%)	11 (11.69%)	1 (1.0%)
	Total	4665(92.6%)	304(6.06%)	60 (1.19%)
Child birth Order	1-5	3547 (93.05%)	221 (5.82%)	43 (1.13%)
	6-10	1061 (91.9 %)	77 (6.70%)	16 (1.41%)
	Above 10	57 (90.72%)	5 (8.67%)	1 (1.58%)
	Total	4665(92.6%)	304(6.06%)	60 (1.19%)
Duration of breastfeeding	Ever breastfed	2328 (92.92%)	142 (5.68%)	35 (1.39%)
	never breastfed	225 (91.87%)	18(7.58%)	2 (0.81%)
	Still breastfeeding	2111 (92.67%)	143 (1.30%)	24 (1.05%)
	Total	4665(92.6%)	304(6.06%)	60 (1.19%)
	Less than 3	4035(93.27 %)	243 (5.61%)	48 (1.12%)

Number of under-five children	3 and above	629 (89.59%)	62 (8.8%)	11 (1.61%)
	Total	4665(92.6%)	304(6.06%)	60 (1.19%)
Child age in months	0-12 months	1016 (91.82%)	79 (7.15%)	11 (1.05%)
	13-24 months	952 (92.77%)	60 (5.89%)	14 (1.35%)
	25-36 months	902 (92.01%)	68 (6.95%)	10. (1.06%)
	37-48 months	988 (95.0%)	41 (4.0%)	11(1.0%)
	Total	3860 (92.90%)	249 (5.99%)	46 (1.11%)
Source of drinking water	Non Improved	2960 (93%)	196 (6.17%)	24 (0.78%)
	Improved	1613(92%)	100 (5.61%)	32 (1.83%)
	Other	91 (88.95%	9 (8.3%)	3 (2.75%)
	Total	4665(92.6%)	304(6.06%)	60 (1.19%)
Antenatal care	Yes	2555 (91.36%)	198 (7.07%)	44 (1.57%)
	No	2110 (94.5%)	107 (4.79%)	15 (0.71%)
	Total	4665(92.6%)	304(6.06%)	60 (1.19%)

Source; Ethiopia 2019 mini DHS data.

4.3. Multilevel model results

Three levels of ordinal logistic regression were used to identify associated risk covariates of wasting. The first level was children or individuals the second level was households and the last level was EA. STATA and R software were used for data management and analysis.

4.3.1. Intercept only

This is the simplest model that includes only the intercept as a predictor. It's also known as a null model.

Covariates	Coef.	Z	Robust Std. Err	P>|z|	[95% Conf. Interval]	
Constant 1	2.98	14.05	0.21	0.000	2.56	3.40
Constant 2	4.97	15.79	0.31	0.000	4.35	5.59
EA	1.14		0.28		0.70	1.85
HH	0.37		.38		0.05	2.82

The intercept only model indicates that the intercepts 2.98 and 4.97 interpreted as the odds of being in a higher level of wasting an average enumeration area.

4.3.2. Random intercept model

The result of random intercept indicates that out of the included explanatory variables sex of child wealth index, mother education level region, DBF, source of drinking water and antenatal care are significant risk covariates of wasting.

Table 4: Parameter Estimation of random intercept model

Covariates		Coef.	St.Err.	Z	p-value	Odds Rartio	[95% CI]		Sig
Religion (ref: Orthodox)	Protestant	-0.37	0.282	-1.31	0.189	0.69	0.39	1.19	
	Muslim	-0.52	0.285	-1.83	0.067	0.59	0.33	1.03	*
	Other	0.189	0.474	0.4	0.691	1.20	0.47	3.06	
Sex of child (ref: Male)	Female	-0.61	0.128	-4.84	0.00	0.54	0.42	0.69	***
Residence (ref : Urban)	Rural	0.375	0.268	1.4	0.161	1.45	0.86	2.46	
Wealth index (ref: Low income)	Middle income	-0.45	0.202	-2.24	0.025	0.64	0.42	0.94	**
	High income	-0.19	0.2	-0.97	0.333	0.82	0.55	1.22	
Mother Education level (ref: Illiterate)	Primary	-0.36	0.163	-2.23	0.026	0.69	0.51	0.95	**
	Secondary and Above	-0.74	0.297	-2.49	0.013	0.48	0.27	0.85	**
Mother's present marital status (ref :Unmarried)	Married	2.23	2.794	0.8	0.424	9.34	0.04	2232.7	
	Widowed	2.01	2.858	0.7	0.482	7.46	0.027516	2018.278	
	Divorced	2.61	2.809	0.93	0.351	13.72	0.056	3377.8	
Mother's age at first birth (ref: 10-20)	21-30	-0.15	0.149	-1.02	0.309	0.86	0.64	1.15	
	Above 30	-1.88	1.08	-1.74	0.081	0.15	0.018	1.26	*
	Afar	0.77	0.575	1.35	0.178	2.17	0.70	6.69	

Region (ref: Tigray)	Amhara	-0.40	0.345	-1.17	0.244	0.67	0.34	1.31	
	Oromia	-0.94	0.397	-2.36	0.018	0.39	0.17	0.85	**
	Somali	1.38	0.471	2.93	0.003	3.98	1.58	10.02	***
	Benishangul	-0.45	0.705	-0.64	0.524	0.64	0.16	2.53	
	SNNP	-0.51	0.404	-1.26	0.206	0.56	0.27	1.32	
	Gambella	0.756	0.839	0.9	0.368	2.13	0.41	11.02	
	Harari	1.913	0.807	2.37	0.018	6.77	1.39	32.91	**
	Addis Ababa	0.274	0.522	0.52	0.600	1.31	0.47	3.65	
	Dire Dawa	-0.09	1	-0.1	0.924	0.90	0.12	6.45	
Birth order (ref: 1-5)	6-10	-0.04	0.156	-0.26	0.799	0.96	0.70	1.30	
	Above 10	0.27	0.501	0.53	0.594	1.30	0.48	3.48	
DBF(ref: Ever breasted)	Never breastfed	0.06	0.29	0.21	0.837	1.06	0.60	1.87	
	Still breastfeeding	0.35	0.137	2.57	0.01	1.42	1.08	1.86	**
Number of under-five (ref: Less than 3	3 and above	0.133	0.185	0.72	0.473	1.14	0.79	1.63	
Source of drinking (ref: Non improved)	Improved	-0.34	0.163	-2.07	0.038	0.71	0.51	0.98	**
	Other	-0.04	0.42	-0.1	0.917	0.96	0.41	2.18	
Antenatal care (ref: No)	Yes	-0.37	0.152	-2.47	0.013	0.69	0.51	0.92	**
	*** *p<0.01*, ** *p<0.05*, * *p<0.1*								

4.3.3. Random coefficient model

Region randomly taken as random effect and random coefficient model was executed. The results show that sex of child, wealth index, mother's education level, DBF, antenatal care and source of drinking water are significant risk covariates of wasting. (Result presented in appendix Table 15).

4.3.4. Model selection criteria

Table 5: Model selection criteria

Model	AIC	BIC
Intercept only	2827.4	2853.6
Random intercept model	2745.9	2981.7
Random coefficient model	2790.1	3012.8

In statistical modeling, the AIC and the Bayesian Information Criterion BIC are used to compare models, while models with lower values indicate a better fit. The random intercept model has the lowest AIC 2745.9 and BIC 2981.7, suggesting the random intercept model fits the data well. While the random coefficient model also has a lower AIC than the Intercept Only Model, its BIC is higher, indicating it may be more complex without a corresponding increase in fit. Therefore, based on these criteria, the Random Intercept Model is the better fit for the data. Interpretation and discussion were done for the random intercept model (presented in table 4 page 32).

4.3.5. Selection of number of parameters

Table 6: Selections of parameters

Models	AIC	BIC
Null model	2827.44	2853.64
Intermediate model	2785.33	2844.27
Full model	2248.63	2350.22

Since the random intercept model fits the data well to select a number of parameters again criteria were used to identify the number of parameters. AIC and BIC aim to balance model goodness and penalize unnecessary parameters (Kumar, 2023). Null Model: With the highest AIC (2827.44) and BIC (2853.64), the null model likely has the poorest fit among the three. It serves as a baseline model with no predictors other than the intercept. Intermediate Model: This model has lower AIC (2785.33) and BIC (2844.27) values compared to the null model, indicating a better fit. The full Model: It has the lowest AIC (2248.63) and BIC (2350.22), suggesting it is the best fitting model among the three.

4.3.6. The intra-class correlation

The residual intra-class correlation (ICC) for the model is estimated to be 0.025 for the EA group and 0.092 for the HH group. The standard errors and 95% confidence intervals are also provided. The ICC measures the correlation between the latent responses from the same group, indicating the degree of similarity in responses within each group. The ICC values are relatively greater than zero suggesting that the responses are somewhat correlated within each group (EA and HH). The LR test indicates that there is a significant variation of the wasting level of children among clusters and households.

Table 7: Intra_class correlation

Residual intra-class correlation	ICC	Std.Err.	[95% CI]	
EA	0.025	0.006	[0.015	0.041]
HH	0.092	0.021	[0.058	0.142]

LR test = 44.19 Prob > chi2 <0.001

4.3.7. Test of parallel assumption

The Brant test is used to assess the parallel lines assumption in ordinal logistic regression, which is the assumption that the relationship between each pair of outcome groups is the same across all levels of the independent variables (Brant, 1990). The Brant test yields a Chi-square statistic of 35.11 with a p-value of 0.323. The p-value is greater than the common alpha level of 0.05, which suggests that there is not enough statistical evidence to reject the null hypothesis. In other words, the test does not provide sufficient evidence to suggest that the parallel lines assumption has been violated. Therefore, it is reasonable to conclude that the proportional odds assumption holds for the model based on this test.

Table 8: Test of Proportional odds assumption

	Chi-square	Df	p-value
Brant	35.11	32	0.323

4.3.8. Model adequacy checking

It is desirable to ascertain whether or not a fitted model adequately describes the data once the model has been fitted. When the cumulative logit model fit well, any collapse of the response categories would also fit well with comparable effects. One method to assess model appropriateness is to investigate each of the binomial models independently, as diagnosing ordinal and multinomial models can be highly challenging (Hosmer and Lemeshow, 2000).

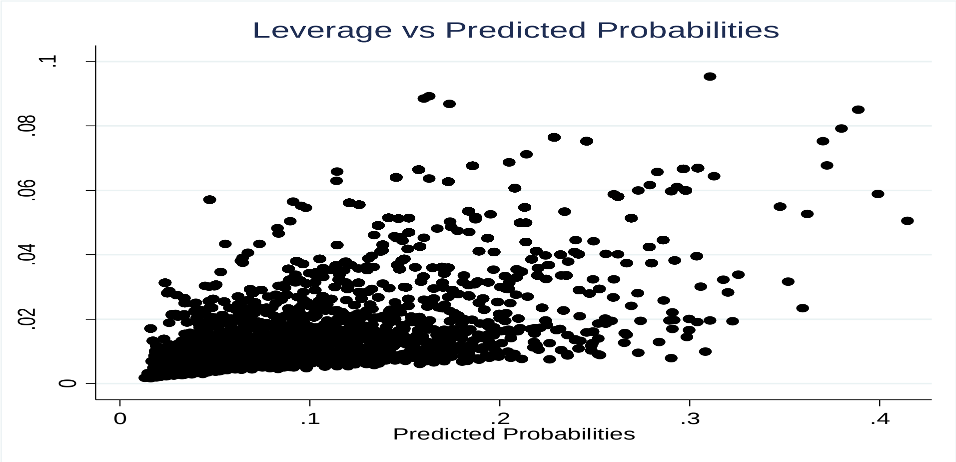

Figure 2: Leverage vs predicted probability

Figure 2 showcases connection between leverage values and the expected probability for each observation within our logistic regression model. Here, the leverage values all fall below one. This finding is particularly encouraging because it implies an absence of outliers. Since none of the leverage values reach one, we can be confident that no single data point has an excessive impact on the model's fit. This strengthens our trust in the model's accuracy and its ability to represent the underlying relationships within the data.

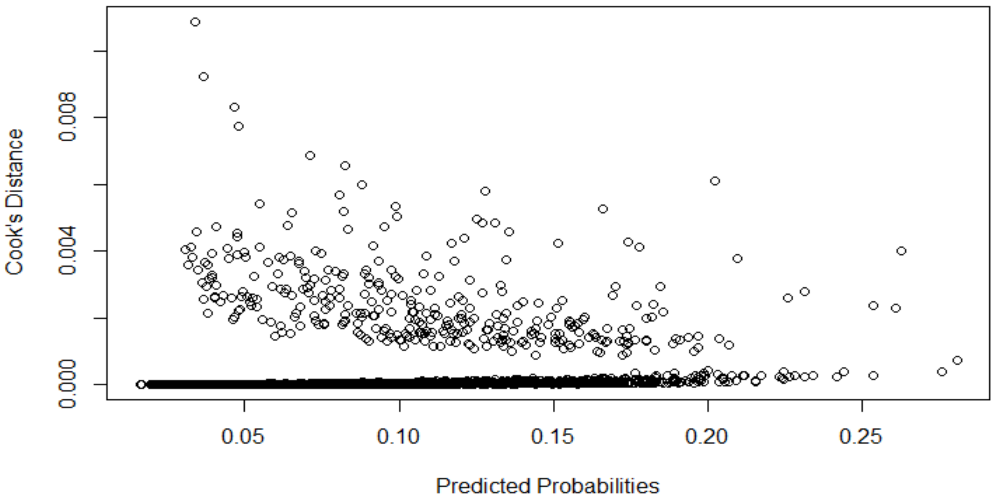

Figure 3: Cook's distance vs predicted probabilities

Figure 3 is the plot of Cook's distance versus the predicted probabilities for each observation in our model. While there are a few data points that appear visually distinct from the others, further analysis shown below reveals these points are not a cause for concern. This is because all the Cook's distance values fall below one, a threshold indicative of influential observations. In simpler terms, even though some points might seem like outliers in the plot, their impact on the model is minimal.

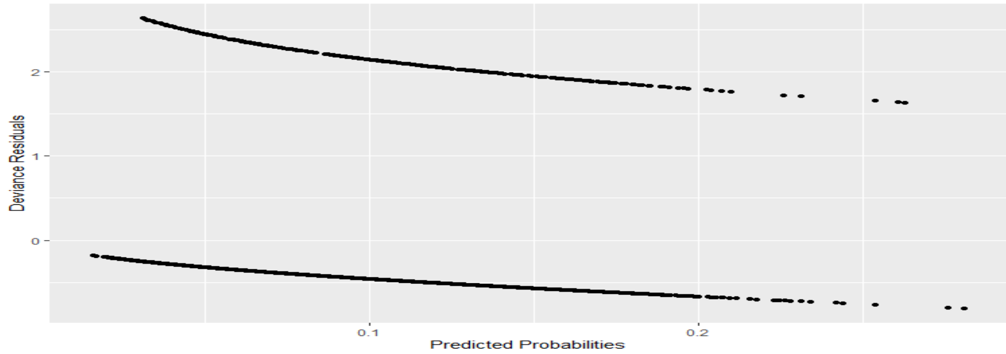

Figure 4: Deviance residual vs predicted probability

Figure 4 above shows the plots of deviance residuals versus predicted probabilities of all observations. Few observations lie far away from the rest but all deviance residuals are less than three. Therefore, there is no lack of fit.

4.3.9. Interpretation of results of random intercept model

When the proportional odds assumption holds, interpreting the coefficients in ordinal logistic regression through odds ratios becomes a powerful tool. It allows us to understand how changes in the explanatory variables influence the likelihood of individuals falling into different categories of the ordinal outcome variable (Hosmer and Lemeshow, 2000). The interpretation of the significant covariates is presented below.

In this study, if the p value of the predictor variables is less than 5% we consider it as significant covariate of wasting. The model explores various covariates affecting the wasting level of children. Sex of the child plays a role, with female children being 0.54 times less likely to be severely/moderately wasted compared to male children, with a 95% Confidence interval (0.42 0.69) holding all other variables constant. This could reflect inherent biological differences or cultural factors in care practices. At a 5% of significance level wealth index is a critical determinant; children from middle-income families are 0.64 times less likely to be wasted than those from low-income families, indicating the protective effect of improved economic status. Mother's education significantly impacts child wasting. Children of mothers with primary education are 0.69 times less likely to be wasted compared to those with illiterate mothers holding all other variables constant. The effect is even stronger for mothers with secondary education and above, mothers have secondary and above education is 0.48 times less likely to have children with moderately/severely wasted holding all other variables constant. Regional differences are evident, with children from the Somali region being 3.98 times more likely to be the upper level of wasting level compared to the reference group(Tigray) holding all other variables constant. Conversely, children from Oromia are 0.39 times less likely to be upper level of wasting level by holding all other variables constant. Being Harari region is 6.77 times more likely to be upper level of wasting level compared to the reference group(Tigray) by holding all other variables constant. Breastfeeding status does not show significant effects, but still breastfeeding increases the odds of wasting (1.42 times), which may indicate issues with weaning practices. The source of drinking water is significant, with children having access to improved sources being 0.71 times less likely to be moderately or severely wasted by holding all other variables constant, underscoring the role of clean water in child health. Lastly, antenatal care shows a protective effect, with children whose mothers received antenatal care being 0.69 times less likely to be wasted, emphasizing the importance of maternal healthcare during pregnancy and holding all other variables constant.

4.4. Model diagnosis

4.4.1. Goodness of fit

The likelihood-ratio test output shows a comparison between a full model and a reduced model, with a test statistic (LR chi2) of 121.43 and a p-value of less than 0.0001. This indicates that the full model, which includes additional predictors, provides a significantly better fit to the data than the reduced model. The result is highly significant, suggesting that the predictors in the full model contribute to explaining the variability in the response variable. In essence, the full model’s complexity is justified, as it captures important information that the reduced model misses. This test supports the inclusion of the additional predictors in our analysis, as they enhance the model’s explanatory power

Table 9: Goodness of fit

LR chi2	121.43
Prob > chi2	<0.001

4.4.2. Multicollinearity

The result of variance inflation factors (VIFs) indicates absence of multicollinearity among the predictor variables in the model. VIFs measure how much a predictor's variance is inflated by its correlation with other predictors. As a rule of thumb, VIFs greater than 10 suggest potential multicollinearity issues. In our case, all the VIFs are reported to be less than 10, with an average VIF of 2.43. This well below the concerning threshold signifies that there's no excessive collinearity between the predictor variables. Overall, the VIFs provide encouraging evidence that the predictor variables in the model are likely statistically independent and suitable for further analysis.

Table 10: Multicollinearity

VIF Mean	2.43

5. DISCUSSION

Sex: The study aligns with prior research by demonstrating that girls are less susceptible to wasting compared to boys. Biological factors might play a role, but social and cultural norms regarding feeding practices could also be influential. Past studies have highlighted potential gender biases in food allocation within households, which could disadvantage boys. Our research aligns with previous studies that emphasize the multifaceted nature of childhood malnutrition. While factors like maternal education and religion undoubtedly play a role, as highlighted in Birhan and Belay's (2021) work on underweight children in Ethiopia, our findings similar results from other research. Just like these studies identified non-biological determinants, our analysis reveals that sex is a significant factor influencing a child's vulnerability to wasting. This underlines the importance of biological factors to develop effective interventions for tackling childhood malnutrition. Jane et al (2008), done research entitled Determinants of Children's Nutritional Status in Kenya and found supportive result. showed that boys suffer more malnutrition than girls. Boys may be at a higher risk in some contexts. Biological factors like faster growth rates in boys might increase their nutritional needs, making them more vulnerable to deficiencies. Additionally, some cultures prioritize food for boys, leading to unequal access for girls. Early weaning of boys and potential neglect due to gender bias can further worsen their situation. However, it's important to remember that poverty and lack of resources are major underlying causes for all children. More research is needed to fully understand the interplay of biological and social factors, but ensuring equitable access to food and healthcare for both genders, along with promoting gender equality within communities, is crucial to address childhood malnutrition.

Education: The strong protective effect of maternal education on child wasting is consistent with previous research. Educated mothers might have better knowledge of child nutrition, hygiene practices, and access to healthcare services. They might also be more empowered to advocate for their children's needs and secure resources. Investing in girls' education can have a ripple effect, improving not only their own well-being but also the health and nutrition of their children. This finding supported by (Birhan and Belay, 2021) used multilevel ordinal logistic regression model to identify associated risk covariates of underweight among under-five children in Ethiopia. They found that educational level of mother, religion, had significant effect on underweight among under-five children in Ethiopia. A research done in Bangladesh also support our finding that is parental educational qualification, were all major factors of the WHZ score of a child (Hossain et al., 2022). (Mbogori & Muriuki, 2021) study reveal mothers with no education are highly affected by wasting and stunting. In contrast, mothers with secondary or higher education were significantly more likely to be overweight or obese. Our result supported by Masibo (2013), carried a research on Trends and Determinants of Malnutrition among Children Aged 0-59 Months. Maternal education was a significant determinants of child wasting. According to (Gudu et al., 2020), paternal lack of formal education was independently associated with wasting. (Jane et al, 2008) find consistent results indicating that maternal education is a more important determinant of children's nutritional status than paternal education. Tanyi in 2007 in Sudan found that maternal education was strongly related to wasting which is consistent with our result. Another master's thesis done in Djibouti by Aden entitled Risk Factors to Malnutrition in Children Under Five Years Old in Djibouti, Africa showed low education of mothers has a direct relationship with wasting (Aden, 2010)

Regional disparity: The stark difference in wasting risk between regions underscores the importance of geographical context. Areas like the Somali and Harari region likely face challenges related to food insecurity, limited access to clean water and sanitation, or inadequate healthcare infrastructure. These factors can all contribute to increased vulnerability to wasting. Effective interventions must be tailored to address the specific needs and challenges of each region. This finding is consistent with (Kuse & Debeko, 2023) who used secondary data from EDHS, 2016, was employed, a total of 7960 under-five children in the analysis. The general spatial analysis was performed to explore the spatial distribution of malnutrition among under-five within and between the regions of Ethiopia (Kuse & Debeko, 2023). They found a significant spatial variation of malnutrition across the regions and Zones of Ethiopia (Kuse & Debeko, 2023). The significant source of spatial variation of malnutrition in children under five was associated with the mother's education level, and region. The result of Dabale and Sharma showed the existence of significant variations in the prevalence of wasting among the regions in Ethiopia (Dabale & Sharma, 2014).

Wealth index: Studies show a clear link between wealth index and child wasting. Children from poorer households, indicated by a lower wealth index, are significantly more likely to experience wasting compared to wealthier counterparts. This is likely due to limited access to nutritious food, clean water, and sanitation facilities associated with poverty. These factors contribute to malnutrition, making children from lower socioeconomic backgrounds more vulnerable to wasting, a severe form of malnutrition characterized by rapid weight loss and muscle wasting. A research done in Kenya on Trends and Determinants of Malnutrition among

Children Age 0-59 Months got supportive result, that is the more wealthier the les become wasted (Masibo, 2013). (Mbogori & Muriuki, 2021) in Kenya found wasting and stunting were significantly higher in children born to families with lower wealth index. (Jane et al, 2008) find supportive result. Household assets are also important determinants of children’s nutritional status. A research done by (Tanyi, 2007) an identifying the determinants of malnutrition in two states in Sudan found similar result: that is for every increase of 100 dinars of a household income, the children in the household are approximately two-thirds times (0.662) less likely to be wasted. Tesfaw (2008), found a similar result: economic status significantly affects the nutritional status of children in Ethiopia.

Antenatal care: Adequate antenatal care can significantly reduce the risk of wasting in children. Regular prenatal checkups allow healthcare providers to identify and address potential risks during pregnancy, such as maternal malnutrition or infections, that can contribute to low birth weight and a weakened immune system in the newborn. These factors increase the child's susceptibility to wasting later in infancy and early childhood. Antenatal care also equips mothers with knowledge about proper nutrition and hygiene practices, which are crucial for preventing wasting in their children. Our study shows that mothers who took that iron tablet during pregnancy were less likelyhood to be wasted. (Gudu et al., 2020) found similar results mothers not having attended ante-natal were associated with under-nutrition. Multivariate logistic regression models were performed to analyze the determinants of nutritional status among the children in the state of Somalia. Gebremichael & Gebretsadik (2022), showed mothers who didn’t attend ANC follow-up during the last pregnancy were significantly positively associated with the occurrence of wasting among children aged 6-23 months. (Gilano et al., 2023) found a similar result to this study: antenatal care shows a protective effect on wasting.

Breastfeeding: our result reveals that breastfeeding has a positive relationship with wasting level. This may be due to the fact that, breast milk provides essential nutrients, antibodies, and immune factors that protect infants from infections and promote healthy growth. However, there are situations where breastfeeding might be indirectly linked to wasting: HIV/AIDS: In mothers with untreated HIV, the virus can be transmitted through breast milk. In such cases, formula feeding with proper hygiene practices might be recommended to protect the child's health. Maternal Malnutrition: If a mother is malnourished herself, the quality of her breast milk might be compromised, potentially reducing its effectiveness in preventing wasting in the child. Jomah (2018), carried out a research about determinants of child malnutrition in Sudan and found out that, in contrast to our result, breastfeeding factors and one factor of each of hygiene, additional feeding, sanitation and care and maternal health and nutrition factor respectively to have an important role in reducing malnutrition among under-five children. Gebremichael & Gebretsadik (2022), researched the prevalence of wasting and associated factors among children aged 6-23 months in Garowe, Puntland, Somalia to assess the prevalence of wasting and associated factors among children aged 6-23 months and reported similar results with us that is breastfeeding initiation after some hour of birth has greater than one odds ratio of being wasted.

Source of drinking water: the study showed negative relationship of wasting level and drinking improved source of water. This implies access to improved drinking water, like piped water or protected wells, plays a crucial role in preventing wasting in children. Contaminated water can harbor harmful bacteria, viruses, and parasites that cause diarrhea and other illnesses. These illnesses can lead to dehydration, nutrient loss, and ultimately, wasting. By providing clean drinking water, we reduce the risk of these infections, allowing children to better absorb nutrients and maintain healthy weight. This highlights the importance of water quality and sanitation interventions alongside promoting breastfeeding and proper nutrition practices to effectively combat childhood wasting. The study done by (Tanyi, 2007) agrees with this. He found main source of water is strongly related to wasting; children in households with unsafe sources of water were 2.6 more likely to have wasting than those with piped in/tube wells as their main source of water. This is Consistent with the result of Tesfaw (2008), source of drinking water is one of the factors that are significantly directly related with the nutritional status of children in Ethiopia.

6. CONCLUSION AND RECOMMENDATION

6.1. Conclusion

The analysis of child wasting prevalence in Ethiopia using the 2019 mini DHS data reveals several key findings. The majority of children (92.76%) have a normal wasting level, while 6.06% are moderately wasted and 1.19% are severely wasted. The prevalence of wasting varies significantly by region, with Oromia having the highest normal rate and Somali having the highest severe wasting rate. Urban residence is associated with a slightly higher normal rate compared to rural areas, and low-income families have a lower normal rate and higher wasting rates compared to middle and high-income groups. Children of illiterate mothers have a lower normal rate and higher wasting rates than those whose mothers have primary or higher education levels.

The multilevel ordinal logistic regression of the random intercept model shows that the full model provides the best fit as suggested by AIC and BIC criteria. The intra-class correlation (ICC) is estimated to be 0.025 for Enumeration Areas (EAs) and 0.092 for households

The significant predictors of child wasting include the sex of the child, wealth index, mother's education level, region of residence, still breastfeeding, source of drinking water, and antenatal care. The results highlight the importance of addressing these factors in order to improve child nutrition and reduce wasting levels in Ethiopia.

6.2. Recommendation

Based on the analysis of child wasting prevalence and risk covariates in Ethiopia using the 2019 mini DHS data, the following recommendations were made:

Target high-risk regions: Interventions should prioritize regions with higher wasting rates, such as Somali, Afar, and Harari, to address the severe wasting issue.

Focus on low-income households: Children from low-income families have higher rates of moderate and severe wasting. Improving access to nutritious food, providing supplementary feeding programs, and increasing household income through social protection measures can help reduce wasting in this group.

Promote maternal education: Children of illiterate mothers have higher wasting rates. Investing in girls' education and providing nutrition education to mothers can empower them to make informed decisions about their children's health and nutrition.

Strengthen antenatal care services: The analysis shows that antenatal care is associated with lower wasting rates.

Encourage optimal breastfeeding practices.

Improve access to clean water and sanitation: Non-improved drinking water sources are associated with higher wasting rates. Investing in water, sanitation, and hygiene (WASH) infrastructure can contribute to better child health and nutrition outcomes.

By implementing these recommendations and addressing the key determinants of child wasting, Ethiopia can make significant progress in reducing the burden of malnutrition and ensuring the health and well-being of its children.

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Appendix

Table 11: VIF

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. estat vif
```

Variable	VIF	1/VIF
Religion		
2	2.39	0.417784
3	3.11	0.321913
4	1.20	0.830588
2.Sex_of_c~d	1.01	0.990574
2.Residence	1.85	0.540136
Socio_ec		
2	1.22	0.820262
3	2.05	0.486844
Mother_Edu1		
2	1.32	0.755114
3	1.59	0.630018
Marital_St~1		
2	10.07	0.099290
3	2.93	0.340935
4	8.25	0.121263
mother_age~t		
2	1.10	0.905574
3	1.05	0.955141
Region		
2	3.30	0.303260
3	1.94	0.515536
4	2.99	0.334839
5	3.23	0.309775
6	2.34	0.427576
7	2.99	0.334303
8	2.43	0.411427
9	2.49	0.402153
10	1.91	0.524394
11	2.30	0.433856
Birth_O		
2	1.15	0.866787
3	1.02	0.981057
DBF		
94	1.08	0.927957
95	1.07	0.930253
2.underfive	1.12	0.893643
Mean VIF	2.43	

Table 12: Mixed-effects ologit regression

WHZ_Ordinal	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Religion (ref: Orthodox)	0	.	.	.	.	.	
Protestant	-.371	.282	-1.31	.189	-.923	.182	
Muslim	-.522	.285	-1.83	.067	-1.08	.036	*
Other	.189	.474	0.40	.691	-.741	1.118	
sex of child (ref: Male)	0	.	.	.	.	.	
female	-.618	.128	-4.84	0	-.868	-.368	***
type of place of residence (ref :	0	.	.	.	.	.	

Urban)							
rural	.375	.268	1.40	.161	-.15	.901	
Wealth index (ref: Low income)	0	.	.	.	.	.	
Middle income	-.451	.202	-2.24	.025	-.846	-.056	**
high income	-.194	.2	-0.97	.333	-.587	.199	
Mother Education level (ref: Illiterate)	0	.	.	.	.	.	
Primary	-.362	.163	-2.23	.026	-.681	-.043	**
Secondary and Above	-.739	.297	-2.49	.013	-1.321	-.157	**
mother's present marital status (ref :Unmarried)	0	.	.	.	.	.	
Married	2.235	2.794	0.80	.424	-3.24	7.711	
Widowed	2.009	2.858	0.70	.482	-3.593	7.61	
Divorced	2.619	2.809	0.93	.351	-2.888	8.125	
mother's age at first birth (ref: 10-20)	0	.	.	.	.	.	
21-30	-.151	.149	-1.02	.309	-.443	.14	
Above 30	-1.884	1.08	-1.74	.081	-4	.233	*
region (ref: Tigray)	0	.	.	.	.	.	
Afar	.774	.575	1.35	.178	-.353	1.901	
Amhara	-.402	.345	-1.17	.244	-1.078	.274	
Oromia	-.938	.397	-2.36	.018	-1.716	-.159	**
Somali	1.381	.471	2.93	.003	.458	2.305	***
Benishangul	-.449	.705	-0.64	.524	-1.83	.932	
SNNP	-.511	.404	-1.26	.206	-1.302	.281	
Gambella	.756	.839	0.90	.368	-.888	2.4	
Harari	1.913	.807	2.37	.018	.332	3.494	**
Addis Ababa	.274	.522	0.52	.6	-.749	1.297	
dire Dawa	-.095	1	-0.10	.924	-2.055	1.865	
: base 1-5	0	.	.	.	.	.	
6-10	-.04	.156	-0.26	.799	-.345	.265	
Above 10	.267	.501	0.53	.594	-.714	1.249	

DBF (ref: Ever breasted)	0	.	.	.	.	.	
never breastfed	.06	.29	0.21	.837	-.508	.627	
still breastfeeding	.352	.137	2.57	.01	.084	.621	**
number of under-five (ref: Less than 3)	0	.	.	.	.	.	
3 and above	.133	.185	0.72	.473	-.229	.494	
Source of drinking (ref: Non improved)	0	.	.	.	.	.	
Improved	-.339	.163	-2.07	.038	-.659	-.018	**
Other	-.044	.42	-0.10	.917	-.868	.78	
Antenatal care (ref: No)	0	.	.	.	.	.	
Yes	-.375	.152	-2.47	.013	-.673	-.078	**
Constant	4.322	2.821	1.53	.125	-1.206	9.851	
Constant	6.362	2.826	2.25	.024	.824	11.901	**
Constant	.658	.172	.b	.b	.394	1.1	
Constant	.477	.321	.b	.b	.128	1.782	
**** p<.01, ** p<.05, * p<.1*							

Table 13: Test of parallel assumption

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Test of the parallel regression assumption

                    |   Chi2      df   P>Chi2
--------------------+-------------------------
              Brant |  35.11      32    0.323
```

Table 14: Intra-class correlation

Level	ICC	Std. Err.	[95% Conf.	Interval]
EA	.0248448	.006392	.0149637	.0409793
HH|EA	.0916008	.0211567	.0577266	.1423496

Table 15: Random coefficient model

```
Mixed-effects ologit regression                 Number of obs     =      5,164
Group variable:             EA                  Number of groups  =        305

                                                Obs per group:
                                                              min =          1
                                                              avg =       16.9
                                                              max =         36

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(29)     =     149.22
Log likelihood = -1361.0855                     Prob > chi2       =     0.0000
```

WHZ_Ordinal	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Sex_of_child						
female	.5606683	.066061	-4.91	0.000	.4450541	.7063163
Residence						
rural	1.324045	.2690396	1.38	0.167	.8890836	1.9718
Socio_ec						
Middle income	.6368892	.1162613	-2.47	0.013	.4453288	.9108501
high income	.75982	.1368766	-1.52	0.127	.5337924	1.081556
Mother_Edu1						
Primary	.6941696	.1025351	-2.47	0.013	.5196793	.9272475
Secondary and Above	.554113	.1490635	-2.19	0.028	.3270501	.9388203
Marital_Status1						
Married	9.029025	24.82001	0.80	0.423	.0412821	1974.788
Widowed	8.126309	22.79128	0.75	0.455	.0333111	1982.43
Divorced	12.71998	35.13608	0.92	0.357	.0566545	2855.872
mother_age_at						
21-30	.8916385	.1210907	-0.84	0.398	.6832658	1.163558
Above 30	.190858	.1997196	-1.58	0.113	.0245464	1.483999
Region						
afar	1.16179	.6261091	0.28	0.781	.4040173	3.340836
amhara	.6723232	.1901745	-1.40	0.160	.3861943	1.170443
oromia	.3471476	.0958956	-3.83	0.000	.202013	.596553
somali	1.967324	.6568553	2.03	0.043	1.022527	3.7851
benishangul	.4683184	.3291777	-1.08	0.280	.1180967	1.85714
snnpr	.5194976	.1514264	-2.25	0.025	.2934067	.9198079
gambela	1.540857	1.371628	0.49	0.627	.2691822	8.820199
harari	8.236095	6.981936	2.49	0.013	1.563642	43.38159
addis adaba	1.198186	.5516337	0.39	0.695	.4860027	2.953993
dire dawa	.5630649	.5800188	-0.56	0.577	.07477	4.240232
Birth_O						
6-10	.9741956	.1383547	-0.18	0.854	.7374948	1.286866
Above 10	1.263051	.5861773	0.50	0.615	.5086063	3.136609
DBF						
never breastfed	1.089105	.2925349	0.32	0.751	.6433336	1.843756
still breastfeeding	1.366077	.1737053	2.45	0.014	1.06473	1.752713
underfive						
3 and above	1.110655	.1818599	0.64	0.522	.8057543	1.530932
source_drinkingW						
Improved	.704602	.1003351	-2.46	0.014	.5330072	.9314396
Other	.9640909	.3669848	-0.10	0.923	.4571987	2.03297
antenatal_care	.6908796	.0970738	-2.63	0.008	.5245684	.9099187
/cut1	3.921042	2.766013	1.42	0.156	-1.500245	9.342329
/cut2	5.87562	2.768629	2.12	0.034	.4492057	11.30203
EA						
var(Religion)	.0001385	2.99e-07			.000138	.0001391
var(_cons)	.3480014	.000191			.3476273	.3483759
EA						
cov(_cons,Religion)	-.0069434	4.87e-06	-1424.77	0.000	-.006953	-.0069339

Table 16: IC of random coefficient model

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Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	5,164	.	-1361.085	34	2790.171	3012.853