Addis Ababa University
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Impact of Breast-feeding and Other Determinants on the Physical Development of Under-five Children In Ethiopia

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This is to certify that the thesis prepared by (Motuma Badassa Nagari) entitled: "*Impact of Breast-feeding and Other Determinants on the Physical Development of Under-five Children In Ethiopia*" submitted in partial fulfilment of the requirements for the Degree of Master of Science in Statistics (Biostatistics) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Abstract

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As it has been active and all time concern of public health, it is the priority to study more about breast-feeding to support the recommendation of global and national health organizations and their stakeholders. Therefore, we designed the study to identify the potential determinants that have significant impact on physical development of children in Ethiopia and indeed we aimed at studying and stress the impact of breast-feeding on the physical development of under five children in the country. We employed multi-level ordinal logistic regression model on BMI categorized into three ordered categories, to study the effects of all covariates at respective levels. We based our study on the 2019 Ethiopian Mini Demographic and Health Survey (2019 EMDHS) collected in collaboration of USAID, ESS and EPHI in 2019 and we accessed the data from DHS program after procedural requirement and getting permission to use the data set only for academic research work purpose as per the terms of agreement of DHS program. The statistical analysis based on the data that consists of 4825 U5 children whose height and weight recorded during the data collection was generated results that show the existence of significant association between covariates and physical development. The major findings show that breast-feeding status: breast-feeding for one year and less (AOR = 1.781, $p < 0.001$), breast-feeding for two years (AOR = 1.144, $p < 0.01$) and breast-feeding for two years and above (OR 0.511, $p < 0.05$) is found statistically significant factor of physical development of U5 children in Ethiopia. Similarly, Vaccination status: partial vaccination (AOR = 0.625, $p < 0.05$) and complete vaccination (AOR = 0.544, $p < 0.05$) is significant factor. Likewise community media access, mother's education level, health facility, family economic status, ANC, PNC, professional delivery assistance, nutritional status, sex, age, residence are statistically significant determinants of U5 children physical development. We forwarded our recommendation to mothers to breast-feed their child at least for two years beginning breast-feeding within an hour after delivery and continue providing only their breast milk for 6 months after birth. My second recommendation is for the government to prioritize expanding health facilities in order to support the continuation of life-cycles from which particularly breast-feeding. Finally, we recommend health centers and professionals to encourage breastfeeding and initiate breast-feeding at hospital; this recommendation stems from the observation that not all children born at hospital are immediately start breast-feeding.

Dedication

Dedicated to Mr. Abbaa Mirgaa

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Table of Contents

List of Figures

List of Tables

Abbreviations and Acronyms

WHO World Health Organization

UNICEF United Nations Children's Fund

USAID United States Aid for International Development

EPHI Ethiopian Public Health Institute

EDHS Ethiopian Demographic and Health Survey

EMDHS Ethiopian Mini Demographic Data

CDC Centre for Disease Control and Prevention

CHAMPS-ETHIOPIA Children Health, Mortality Prevention and Surveillance

DHS Demographic and Health Survey

GLMM Generalized Linear Mixed Model

GLM Generalized Linear Model

TWB The World Bank

ESS Ethiopian Statistics Service

ICF Inner City Fund

CDA Categorical Data Analysis

EA Enumeration Area

HH Household

AIC Akiake's Information Criterion

BIC Bayesian Information Criterion

WRA Women of Reproductive Age

ANC Antenatal care

PNC Post-Natal care

U5 Under-five years children

SNNP South Nation Nationalities and People of Ethiopia

SD	Standard Deviation
UW	Under-Weight
NW	Normal-Weight
OW	Over-Weight
EBF	Exclusive Breast-feeding
RMLE	Restricted maximum likelihood estimator
MMLE	Marginal maximum likelihood estimator
LA	Length for age
WA	Weight for age
HA	Height for age
HC	Head Circumstance
IYCF	Infant and young child feeding
AOR	Adjusted Odds Ratio
OR	Odds Ratio
MCT	Measures of Central Tendency
MD	Measures of dispersion
BMIA	Body Mass Index For Age
WL	Weight for Length
WH	Weight for Height
ACA	Arm Circumstance for Age
HCA	Head Circumstance for Age

Chapter 1

Introduction

1.1 Background of the study

Growth (Development) of infants and children is among the major concern of public health across the world. Its trend is differ based on infants and children condition, mothers condition and related factors. WHO and other Health organization developed tools and techniques to measure and monitor the growth and development milestone and its regularity WHO (2024). The tools are consists physical development (growth) measurement units such as: LA (HA), WA, WL (WH), BMIA, ACA, HCA, SSC, TSA, MDM, WV, LV, HCV. Among all we used BMIA to measure the physical development of infants and children in this study.

Breast-feeding is among the center of focus for governmental organization, humanitarian organizations and health research institutes both nationally and globally. It is the first most expected and source of nutrition for new born infants and recommended to continue for at least two years exclusively for the first 6 months(WHO, 2023b; CDC, 2024). Almost all of global health organization including WHO, keep promoting, advising, encouraging recommending for the first two years of formative development of children and infants. It is suggested by almost all health organization to feed breast milk for at least two years to enable immunity system of infants and children protective enough and to make their comprehensive health more secured.

These days human beings are struggling to mediate between several advantages and disadvantages of world's fast and dynamic changes. These reformations are multifaceted: technological, socio-economical, and other related lean components (Mustafaoglu et al., 2018). As known, it is not strange that, digital world is under formation. During these changes taking place, there are many unclear distinctions between positive and negative sides of the changes. This concept can be supported by a number of examples. Among all aspects of the issue, we focus on its implications, impacts and influence on public health problems as well as our further concern is on child's care culture and practices including dietary system and related issues. This is due to the one of the two prominent events to make mammalians species life cycle continue is breast-feeding(Victora et al., 2016).

Now-a-days, the culture and practice of health care are different from what it was before. During the former centuries, social practices play a crucial role in infants' development. Now everything relies on machine and artificial equipment's. Even though it has many advantages, these transformations harm some feature of useful social practices and cultures like baby care. Infants at their younger age, need parents' interaction other than any things. They start neurological development from their birth; communicate and movements comfortably by their parents' support. Dieting system is also preferred to be breast-feeding at their younger age. Now-a-days many mothers do not spent optimum time with their children for different reason. Some of them do not want to breast-feed (Mustafaoglu et al., 2018).

In addition to reviewing the global and regional status of breastfeeding practice this study attempts also to investigate the effect and impact of breast-feeding practice and related determinants on childhood comprehensive development specifically focusing on physical development.

It is obvious that many health research institutes and international organizations recommend and promote immediate breast-feeding, and encourage its practice. Breast-feeding and its practice plays a positive role in children physical and neurological development. Children development can be measured by tools of body composition health indicator (CDC, 2024; WHO, 2023a). The body composition anthropological arrangement which is function of change in weight and height. Both weight and height are components of growth and or development. The development of children is said to be healthy or not by measuring body mass index (BMI). This decision to determine whether the development observed is healthy or not is made depending on WHO's threshold points of BMI, (Gibson and Campbell., 2017).

In health context, it is said to be physical growth is normal if BMI score lies within 5% and 85% percentile. This percentile corresponds to 18 to 20 for male and 16 to 18 for female based on their age. It indicates unhealthy development for BMI score lies out of an certain specified by WHO. BMI Less than $16Kg/m^2$ is underweight; which indicate less than expected weight for a given weight and $16Kg/m^2 < BMI < 18Kg/m^2$ normal and indicates ideal development similarly BMI greater than $18Kg/m^2$ is said to be overweight and implies that extra weight for given height. Extreme overweight is called obesity which is associated with an increased risk of premature illness and mortality. Obesity itself is a major public health problem and further it is a risk factor for the development of non-communicable diseases (NCDs), cardiovascular diseases, cancer, and diabetes. These disease account for 75% of deaths in 2020. Enhancing and stressing awareness helps prevent obesity and further contribute to preventing chronic diseases in adults. To keep BMI normal is helps reduce diseases (Oliveira et al., 2022; Racette et al., 2017; WHO, 2023a).

For this study, we have used the most popular and commonly used WHO-developed physical development measurement tools. We selected the tools by considering the criteria whether the measurement tools should be the most valid tools for the target population under study that is eligibility to measure the physical development of children in Ethiopia. We have taken this into account because the development of children depends on geographic and genetic factors. For example, the BMI of Chinese children is not the same as that of Ethiopian children. Therefore, it is important to use measurement tools that are most closely appropriate for the target population.

The WHO-developed measurement tools that has been used in this study was considered to be valid, reliable, and appropriate for the target population of the study. These tools allow us to more accurately assess the physical development of children in Ethiopia than other tools developed by different organizations like CDC and IOTF.

In this study, we focus on BMI as a measure of physical development of U5 children. It is a widely accepted and standardized indicator of physical development that can be used to track growth patterns and identify children who may be at risk for health problems.

Growth charts developed by the World Health Organization (WHO) are recommended for international use and are specific to sex and age group. Most of these charts are used for infants and children under two years of age LA (HA), while some are used for children under three years of age WA or under five years of age HC. Among all the growth charts, BMI is recommended by almost all health institutes, including the CDC, WHO, and IOTF. It is inclusively used for assessing physical growth and development in children and adolescents under 20 years of age. BMI is also acceptable for children from all regions of the world. Therefore, BMI was considered as the variable of analysis in this study. It will be taken to be a measurement of physical development because it is a function of the main anthropometric indicators. A BMI value that falls within the recommended range indicates healthy physical growth and development.

1.1.1 Statement of the Problem

It has been an active concern of maternity, child and infants' health that consists agenda of breast-feeding. A number of organization research institutes and humanitarian organizations design programs and projects to promote the issue and to prevent maternity and children disease as well as to reduce death related to the disease. Among several active agendas on the issue breastfeeding is the hottest issue under concern (Gibson and Campbell., 2017).

Most of the researches conducted to identify factors of breast-feeding practice; which is the condition that affect breast-feeding culture and plan. They may reveal potential factors that are related to mother's conditions like: work status and health status. Other researches were undertaken on malnutrition of infants and children focus on stunting, survival rate, as well as mortality rate and their influencing factors. The results of such researches are almost similar. They report that nutrition is significant factor of children survival rate and they also recommend that dieting system of children should be appropriate and right. Otherwise, it leads to health problem. It is right decision and correct recommendation. However, there are rare research findings to strict the essence of family role in child care including breast-feeding practice. This study was undertaken to upgrade the awareness and understanding of all community level in the country towards necessity, its future benefits of breast-feeding for breast-feeder mothers and its benefit for children in the future life time. The study stresses the awareness about breast-feeding and other related supportive dietary system as well as value of spending time with their parents (WHO, 2023b).

Our review of available evidence begins from status of breast-feeding culture that includes early initiation and exclusive breast-feeding status across the globe and in the country under study. As an evidence for this problem, CDC (the center for Disease Control and Prevention) stated that failure to breast-feeding leads to more than 3 bill. USD extra medical cost for infants and mothers in USA, the country where health service is the most reliable (CDC, 2024; Yimer DS, 2021). Recognizing this evidence, it is not difficult to understand that the same problem leads to greater extra cost in developing worlds. In Ethiopia, according to the Ethiopian Public Health Institute (EPHI), only 59% of infants are exclusively breastfed, as recommended by the World Health Organization (WHO) and (UNICEF) (The World Bank, 2023). This statistic, based on the 2019 Ethiopian Mini Demographic and Health Survey (EMDHS), highlights the significant disparity in breastfeeding practices between Ethiopia and the global average (EPHI, 2019; Zeleke and Zemedu, 2023). This disparity has prompted us to investigate breast-feeding practices and its impact on the health and well-being of mothers and infants. Studies have consistently demonstrated the numerous economic, social, and health benefits associated with breast-feeding, underscoring the need for continued research and interventions to promote this vital practice.

1.2 Objectives of the Study

1.2.1 General Objective

The main objective of the study was to identify the potential socio-economic, demographic, geographic and cultural influencing determinants that affects children and infants' physical development.

1.2.2 Specific Objectives

- To identify the association, its strength and direction between covariates and physical development of children.
- To investigate the association between individual level covariates, particularly breast-feeding and physical development of U5 children.
- To identify the the extent to which community level covariates affect variability in children physical development.

- To identify the extent to which household level covariates affect the physical development of children.

1.2.3 Research question

Hence the study attempted to answered the questions as:

1. What are the potential risk factors that affects the physical development of U5 children in Ethiopia?
2. Is breast-feeding significantly influence the physical development in Ethiopia?
3. Are community-level, household-level and individual-level covariance significantly associated with physical development in Ethiopia?

1.3 Significance of the Study

It has been said more that infant's development and its negative indicators like stunting, wasting, early death rate and similar issues are among core objectives of public health projects and program priorities. This study attempts to reveal the reasons behind those painful indicators of public health problems. It will be over-viewed about stunting, wastage, death rate and related phenomena, and their documented factors to adhere the available evidences and to stress positive perception towards breastfeeding and its practice.

A lot of research reports and intervention reports say more about breast-feeding. Still it is necessary to conduct scientific and close examination of its practice to promote its benefit and to update the perception of world's people towards breast-feeding and associated factors. It is still possible to recover maintain positive attitude to the level where it was before. (Mustafaoglu et al., 2018) stated that before these all comprehensive reforms and global dynamic transformation that encompasses both advantage and disadvantage, breast-feeding, its practice and baby care was favorable tasks of parents; which is current recommendations that covers major parts of media promotion, research articles recommendation, projects reports and advice, and expert's suggestions. Currently there is no positive attitude towards the breast-feeding and its practices in contrary to its essence. Specific to our study, the study will stress not only conditions that matter to culture, attitude, and practice of breast-feeding; it also promote its incredible and pervasive benefits.

1.4 Limitation of the Study

This study has a few limitations that should be noted. First, the data used in the study was collected five years ago. Despite it is the most recent EDHS data available, it is not complete EDHS. This is because the complete Ethiopian Demographic and Health Survey (EDHS) which is conducted every five years was not collected since 2016. The data used in this study were collected to fulfill an urgent requirement and is not as comprehensive as the complete EDHS.

Second, the categorization of body mass index (BMI) of under-five children was not calculated based on empirical data collected from Ethiopia. Instead, we adopted the BMI categorization developed by the World Health Organization (WHO) based on longitudinal data from different countries. This may not be the most accurate way to categorize BMI in Ethiopian children, as there may be differences in growth patterns and nutritional status between Ethiopian children and children from other countries (WHO, 2006).

Despite these limitations, we believe that our study provides valuable insights into the relationship between breast-feeding and child malnutrition in Ethiopia. However, future research should address these limitations by using more up-to-date data and by developing BMI categorization standards that are specific to Ethiopian children.

Beside, the study has the limitation due to that it is cross-sectional, which means that it cannot establish causal relationships between the predictor variables and BMI, it is Self-reported data: The data on breast-feeding and other predictor variables were self-reported, which may have led to some bias. Small sample size: The study sample size is relatively small, which may have limited the power of the study to detect statistically significant associations.

Chapter 2

Literature Review

This chapter outlines the essence of available knowledge, consensus, related to the area under study. It highlights the most critical aspects of awareness, understanding and perception about breast-feeding, its practice, benefits for infants and children, for mothers and its impact on multifaceted development and related issues specifically in Ethiopia.

2.1 Breast-feeding, definition and its benefits

The World Health Organization (WHO) defines breastfeeding as the normal and recommended way of providing young infants with the essential nutrients they need for healthy growth and development. The organization states also that, virtually all mothers are capable of breastfeeding, provided they have access to accurate information and receive the necessary support from their family, the healthcare system, and society at large. Breast-milk is acknowledged as the ideal food for infants, as it supplies all the nutrients they require in the appropriate amounts. It promotes breastfeeding, emphasizing its benefits for both the infant and the mother, and calls for a supportive environment that enables and encourages this natural process (Horta et al., 2023; WHO, 2023a).

The Centers for Disease Control and Prevention (CDC) defines breastfeeding as the act of directly feeding a baby breast milk from the mother's breast. Breast-feeding provides ideal nutrition and supports optimal growth and development for infants. In alignment with the recommendations of the American Academy of Pediatrics, the organization advises exclusive breastfeeding for the first 6 months of a baby's life, followed by continued breast-feeding as complementary foods are introduced. It also emphasizes that breastfeeding should continue for at least 1 year or longer, as mutually desired by the mother and infant. Breast-feeding is recognized as the ideal feeding method, as it delivers the necessary nutrients for healthy infant development while promoting a strong bond between the mother and child (CDC, 2024; Victora et al., 2016).

UNICEF (United Nations Children's Fund) defines breast-feeding as "the normal way of providing young infants with the nutrients they need for healthy growth and development. Breast-milk is the natural first food for babies, it provides all the energy and nutrients that the infant needs for the first months of life, and it continues to provide up to half or more of a child's nutritional needs during the second half of the first year, and up to one-third during the second year of life" (UNICEF, 2023). According to the organization breastfeeding is the ideal and natural feeding method for young infants, as breast-milk supplies all the necessary nutrients for healthy growth and development.

It also strongly advocates for breastfeeding, emphasizing that it can continue to meet a significant portion of a child's nutritional requirements well into the second year of life (UNICEF, 2021).

Breast-feeding, its practice is one of the most effective ways to ensure child health and survival (Alimoradi et al., 2014; Ip, 2017). It is articulated and recognized in a number of research reports, national and international health organizations reports and public health projects reports that breast feeding is very essential for both child and mothers. Breastfeeding is critical determinant of infants and children health. Its implications are: healthy cognitive, emotional, and physical development of infants and children. It is safe, clean and contains antibodies which help protect against many common childhood Diseases (WHO, 2023b). It provides incredible advantage in attaining optimal and healthy physical growth, immune system, and cognitive development among infants and children (Victora et al., 2016). The duration and exclusivity of breastfeeding have been linked to favorable physical development indicators such as growth patterns, weight gain, and body mass index (BMI).

Based on these definitions we can conclude statements as such that all mothers can provide their child with breast-milk if they have adequate awareness, support and encouragement to breast-feed and related factors. The breast-feeding is recommended and acknowledged for its completeness nutrition for infants exclusively and should be continue for at least two years. Similarly, it was also said that breast-feeding is highly useful for both infants and mothers in reducing risk of disease and make the children growth Normal and optimum.

The Center for Disease Control and Prevention (CDC, 2024), in addition to that breastfeeding is the best source of nutrients for infants and children, described that it is unique for its complete nutritional composition in breast-milk. It helps in offering optimal nourishment and immunological defense for infants (Alimoradi et al., 2014; Victora et al., 2016). It provides an array of essential nutrients, antibodies, and bio-active compounds that support the healthy growth and development of children during their formative years. It is not only useful for infants but also it is useful for mothers. Breastfed infants are beneficiary in that it reduces risk of obesity, Asthma, type 1 diabetes, Severe lower respiratory disease, Acute Otitis Medi (Ear infection), sudden infant death syndrome (SIDS), gastro intestinal infection (Vomiting and diarrhea). Mothers' benefits from breast feeding practice in that it reduces risks of blood pressure, type 2 diabetes, breast cancer, ovarian cancer and birth spacing (Victora et al., 2016).

2.2 Scientific research evidences on breast-feeding

Breast-milk is the ideal food for infants (WHO, 2023a). Breast milk, due to its complete nutritional content plays a core role in reducing incidence of childhood morbidity and mortality rate (Patel et al., 2018; Hajure et al., 2020). The human body consists of lean mass and fat mass. There are differences in body composition between exclusively breastfed and formula-fed infants and children. This difference may be involved in the protection breastfeeding offers against overweight and obesity throughout the individual's life (CHAMPS-ETHIOPIA, 2021), a recent meta-analysis concluded that exclusively breastfed infants have a 31% lower chance of later developing overweight and obesity. This protection is probably related to the differences in growth between breastfed and formula-fed infants.

Evidences from different source elucidated that a number of individuals, environmental, socio-economic, inappropriate marketing of breast-milk substitutes, and cultural beliefs are factors that make sway over breast-feeding practices and makes it vary from one community to others (WHO, 2023a). The major factors are educational status and nutritional status of mothers (Hajure et al., 2020; Patel et al., 2018). Further, factors such as residence, employment status, availability of healthcare services for mothers are identified as supportive influencing factors breast-feeding practice (Langellier et al., 2014). Additionally, the neuro-protective properties of breast milk have been associated with a reduced risk of neuro-developmental disorders and improved social and emotional development Piñero et al. (2020). It is this variety that leads to deviation from national and international health organization's recommendation towards encouragements and promotions of breastfeeding practices, its duration and principles (Tesfay et al., 2016). These factors directly affect breast-feeding practice, its duration and frequency subsequently impact physical and motor skill development of children.

The feeding method in early life can have a significant impact on the development of body composition. Several studies have found that infants fed dairy-based formula gain weight and increase their body mass index (BMI) more rapidly during the first six months of life compared to infants who are exclusively or predominantly breastfed. However, this excess weight gain in formula-fed infants does not actually represent an increase in adiposity (body fat) as previously believed. Instead, it is due to a progressive increase in lean mass (muscle and organ tissue).

This excess in lean mass can be explained by the fact that formula-fed infants consume more protein in the first six months of life than breastfed infants. A higher protein intake in the first year of life is associated with a greater increase in lean mass (Koletzko et al., 2009). As a result, the hypothesis that the excess adiposity (fat) accumulated during this period is involved in the association between breast-feeding and lower risk of overweight and obesity in the future may be less strong than previously thought. The key point is that the differences in weight and BMI gain between formula-fed and breastfed infants are primarily driven by increases in lean mass, not fat mass, challenging the previous understanding of how infant feeding method impacts long-term obesity risk (Horta et al., 2015).

The formative years of human life, particularly early childhood, are a critical period for cognitive, emotional, and physical development (Cusick and Georgieff, 2016). During this crucial stage, breast-feeding practices serve as an influential determinant of developmental outcomes across multiple domains. Longitudinal and cross-sectional epidemiological studies have underscored the significance of breastfeeding in shaping variations across key areas of development (Silveira et al., 2013).

Breast-feeding has been linked to enhanced cognitive abilities and academic performance in children (Horta et al., 2015). Additionally, breast-feeding appears to positively influence the development of the nervous system and neurological functions (de Paula Freitas et al., 2016). Furthermore, breast-feeding has been associated with a healthier physical developmental trajectory, including aspects such as growth patterns and body composition.

In essence, the available evidence from epidemiological studies suggests that breast-feeding during the formative years of life plays a pivotal role in promoting favorable cognitive, neurological, and physical developmental outcomes in children (Victora et al., 2016). The nature and extent of these developmental advantages associated with breast-feeding underscore its importance as a significant determinant of holistic human development during the crucial early stages of life (Muluneh et al., 2020).

In Ethiopia, breast-feeding practices are shaped by a complex combined interplay of socioeconomic, cultural, and healthcare challenges. Under-nutrition among mothers, traditional weaning practices, and closely spaced pregnancies are all interconnected factors that contribute to sub-optimal breast-feeding practices. This results in little proportion of infants in Ethiopia being exclusively breastfed for the first six months of life, which is below the global average (WHO, 2023g). Improving breast-feeding practices in Ethiopia is essential for reducing infant mortality and malnutrition. Interventions to improve breast-feeding practices should focus on addressing the underlying socioeconomic, cultural, and healthcare factors that contribute to low breastfeeding rates (Gebeyehu et al., 2023).

UNICEF, WHO, CDC, CHAMPS and other children and maternity health organization and research institutes recommend breast milk for infants and children immediately from birth to at least first two years of their formation time. However, deviance from the recommendation is seen worldwide. It is reported that larger proportion of infants are not breastfed as per the recommendation; thus, breast-feeding promotion intervention is actively conducted by all organization and governments. However, the awareness and consensus of breast-feeding and its practice is misunderstood in different way. It is seen as backwardness in developed world and urban resided community; therefore, they cease very soon after giving birth or they never feed breast milk at all (Victora et al., 2016). Most mothers stop feeding breast milk very early due to different reasons like: working condition, inadequacy of producing breast milk, medical problem, next pregnancy (CDC, 2024). Due to this 44% of infants exclusively breastfed and 56% of them never breastfed or partially breastfed globally (WHO, 2023b). Ethiopian Public Health organization (EPHI, 2019), reported that only 59% of infants exclusively breastfed. World Bank's data also enhanced this fact in aiming at seeking for intervention to promote breast-feeding practice and to reduce health problem due to lack of breastfeeding (The World Bank, 2023)

Lack of malnutrition, mainly breast-feeding contributes 45% of child and infants' death worldwide. According to (Victora et al., 2016; Gebeyehu et al., 2023; Mohammed et al., 2020), about 832,000 to 1.4 mill children's lives can be saved every year among children under 5 years, if all children 0–23 months are optimally breastfed (WHO, 2021). Similarly, about 20,000 WRA will be saved from breast cancer per year if breastfeeding is upgraded to approximately universal Lack of optimal breast-feeding contributes to larger proportion of crude mortality rate (CDC, 2024; WHO, 2023a; CHAMPS-ETHIOPIA, 2021). Economically, breast-feeding practice adds more than 3 billion USD medical cost of infants and mothers per year . This case is intuitively more severe Ethiopia even though not reported. Further, non-alignment to recommended breast-feeding practices is associated with a risk of morbidity, stunted, and wasted growth among under-five years children (Tewabe and Mekuria, 2019).

Researches has demonstrated the positive impacts of breast-feeding on child health, but further investigation is needed to identify the specific factors that mediate or moderate the relationship between breast-feeding practices and physical development outcomes in children under five years of age (Victora et al., 2016). While previous studies have identified factors influencing breast-feeding and child care culture and practices, few have examined the subsequent impact of these factors on children's physical and cognitive development (Rollins et al., 2016). Additionally, research focusing on diverse populations and the role of community-level interventions is essential for a comprehensive understanding of this complex relationship (Kramer and Kakuma, 2012). This study, therefore, was conducted to address these problem by filling the gap of empirical data driven association between breast-feeding and physical development of U5 children in the literature by examining the mediating and moderating factors that influence the relationship between breastfeeding practices and physical development outcomes in children under five years of age in a diverse population.

Furthermore, factors, such as access to supportive lactation programs, healthcare infrastructure, and policy interventions, play a key role in fostering optimal physical growth trajectories across diverse populations through improving awareness about breast-feeding and encouraging it (Rowe-Murray and Fisher, 2002; Patel et al., 2018). Studies have provided robust evidence of the enduring physical benefits of breastfeeding across diverse cultural and demographic contexts. These studies have elucidated the far-reaching implications of exclusive breastfeeding in reducing childhood stunting, improving motor development, and safeguarding against preventable infectious diseases, thus critically contributing to sustained physical well-being during the early years of life (Piñero et al., 2020)

Most literature indicates that the economic status of parents has a significant impact on the physical development of children. It was also articulated that children from lower socioeconomic backgrounds families may face challenges that affect their physical health and development. It was found that children from low-income families were more likely to experience food insecurity, which can lead to inadequate nutrition and poor physical health. Additionally, limited access to healthcare services due to financial constraints can result in untreated health conditions that may hinder a child's physical development. Furthermore, the stress associated with economic hardship in families can also have negative effects on children's physical health. Chronic stress can impact children's immune systems, making them more susceptible to illnesses and affecting their overall well-being.

Among many areas related to children development, stunting is the major one that remains active area of study. It is the problem of physical development abnormality that is less assessed by height for their age. According to (Muche and Dewau, 2021), it was revealed that about 38% of Ethiopian children are stunted; that means their height for their age is under standard quantity set by WHO. it was also stated that stunted children suffer from irreversible physical and cognitive damage which stems from stunted growth and consequently affects their adulthood and even pass to the next generation development conditions (De Onis and Branca, 2016). These literature have not shown the role of breast-feeding in linear growth (physical development) but have dealt with malnutrition collectively. Therefore, in this study we stressed breast-feeding and we have shown its role in linear development.

As far as our review was concerned, most of researches conducted on breast-feeding and and associated areas are systematic meta studies that are based on collecting evidences from published literature and generate advanced evidence to support the practice and strengthen the recommendation of international and national health institutions and health programs. Very limited empirical data-based researches conducted published are available. Another issue is that most of studies undertaken in the area are focused on breast-feeding practice and its association with its determinants but not the further impact on childhood development and future health benefits.

This study attempts to address three critical gaps in the field of breast-feeding: To raise community awareness BY providing evidence-based data on the multifaceted benefits of breastfeeding for both children and mothers. This will supplement existing meta-analyses and empower communities with the knowledge they need to make informed decisions about infant feeding. Additionally, it incorporates BMI directly into the analysis of children's physical development, alongside percentiles and other scores. Lastly, this research generates robust evidence to counter arguments against breast-feeding.

Chapter 3

Data and Methodology

3.1 Data

The data utilized in this study originate from the 2019 EMDHS, conducted by in collaboration with the (ESS) and the Federal FMOH. Financial support for the survey was provided by the WB, USAID, and UNICEF. Technical assistance was offered by ICF through The DHS Program. Access to the data was granted following a formal request and was permitted solely for the purpose of analysis within the framework of a thesis-based agreement adhering to the terms outlined by the DHS Program (EPHI, 2019; The World Bank, 2023; Gebeyehu et al., 2023).

The survey was primarily aimed at providing up-to-date estimates of key demographic and health indicators, including contraceptive use, maternal and child health, mortality rates, child nutrition, and other health issues. It also measured maternal and neonatal morbidity and mortality and associated factors such as antenatal and delivery care. Additionally, it collected information on health-related matters such as breastfeeding, maternal and child care, children's immunizations, and childhood diseases. Finally, it assessed the nutritional status of children under age 5 by measuring weight and height. These measurements used in computation of BMI.

This comprehensive data set is likely to be adequate for our study, as it contains all the variables required for the analysis. To use such secondary data, it is important to note and have details about the data set, such as the sample size, data collection methods, or data quality. These factors should also be considered when assessing the adequacy of the data set for the study. For example, if the sample size is too small, the results of the study may not be generalized to the larger population. If the data collection methods are not rigorous, the data may be biased or inaccurate. And if the data quality is poor, the results of the study may be unreliable. Therefore, it is important to carefully evaluate the data set before using it for the proposed study. This evaluation should include an assessment of the sample size, data collection methods, and data quality.

The sampling design utilized for the survey was multi-level or hierarchical type of sampling methods. Enumeration areas (EAs) created for the 2019 (EPHC), conducted by the (ESS) was used as primary sampling unit; from each EAs systematically selected, households were selected and from each household, data were collected from each eligible children under five years old. Totally 305 (93 from urban and 212 from rural) EAs selected from a total of 149,093 EAs. On average, there are 131 households in each EAs and probabilistic systematic sample of 30 households were selected from each EA and then all eligible children (U5 children) were observed and data on anthropometry was collected from them. Thus more than one U5 children could be found in a single household. The hierarchical structure of this methods was explained structurally to make more clear insight about how data was generated in (AppendixA).

3.1.1 Data Layout for three-level categorical data

The data generated using the above explained sampling methods were tabulated and presented in a long format and wide format; we selected the long format for our convenience. All children from whom data was collected were assigned values that identifies them uniquely from others; this variable was named as "caseid" and it was built up from combination of EA number, HH number in the EA, the child line number in the HH so as it could uniquely define each child. As it was presented in the table 3.1 below, the first column represents the i^{th} EA, the second represents j^{th} HH in i^{th} EA and the third represents k^{th} child in j^{th} HH and i^{th} EA. It is possible to understand that the last column the same as the representation of the data in digital format.

Table 3.1: Data layout for three-level clustered data.

Level 3 (i)	level 2 (j)	level 1 (k)	Respnose ($Y_{j(i)k}$)
i	j(i)	j(i)k	
1	1(1)	1(1)1	$Y_{1(1)1}$
		1(1)2	$Y_{1(1)2}$
		...	... ...
		1(1)k	$Y_{1(1)k}$
	2(1)	2(1)1	$Y_{2(1)1}$
		2(1)2	$Y_{2(1)2}$
		...	...
		2(1)k	$Y_{2(1)k}$
	...	...	...
	j(1)	j(1)1	$Y_{j(1)1}$
		j(1)2	$Y_{j(1)2}$
		...	...
		j(1)k	$Y_{j(1)k}$
2	1(2)	1(2)1	$Y_{1(2)1}$
		1(2)2	$Y_{1(2)2}$
		...	...
		1(2)k	$Y_{1(2)k}$
	2(2)	2(2)1	$Y_{2(2)1}$
		2(2)2	$Y_{2(2)2}$

Continuation of Table 3.1			
Level 3 (i)	level 2 (j)	level 1 (k)	Responses ($Y_{j(i)k}$)
		...	...
		2(2)k	$Y_{2(2)k}$
	...	...	...
	j(2)	j(2)1	$Y_{j(2)1}$
		j(2)2	$Y_{j(2)2}$
		...	...
		j(2)k	$Y_{j(2)k}$
...	...	...	...
i	1(i)	1(i)1	$Y_{1(i)1}$
		1(i)2	$Y_{1(i)2}$
		...	...
		1(i)k	$Y_{1(i)k}$
	2(i)	2(i)1	$Y_{2(i)1}$
		2(i)2	$Y_{2(i)2}$
		...	...
		2(i)k	$Y_{2(i)k}$
		....	....
	j(i)	j(i)1	$Y_{j(i)1}$
	j(i)	j(i)2	$Y_{j(i)2}$
	...	...	...
		j(i)k	$Y_{j(i)k}$
...	...	....	....
N	1(N)	1(N)1	$Y_{1(N)1}$
		1(N)2	$Y_{1(N)2}$
		...	...
		1(N)k	$Y_{N(1)K}$
	...	...	...
	j(N)	j(N)1	$Y_{j(N)1}$
		j(N)2	$Y_{j(N)2}$
		...	...
		j(N)k	$Y_{j(N)K}$
In our case $Y_{N(J)K} = Y_{J(305)K} = 4825$			

3.2 Measurement tools for physical development (growth charts)

The development of children from birth is a complex issue influenced by various factors and encompassing multiple components. It is a major topic of debate among pediatricians, researchers, and other concerned parties. Disagreements exist between professional groups regarding the indicators of development. Health professionals and organizations hold diverse beliefs and rely on different measurement tools to assess physical development. Notably, the CDC has developed a tools to measure physical development for U5 children that differs from the one developed by the World Health Organization (WHO).

According to (WHO, 2023c) and most of researches on the area, it was explained that the community lacks a shared understanding of healthy child development. Many believe that fat infants and children are healthier, a belief supported by the community's intuition. However, there is no scientific evidence to support this belief. In fact, research has shown that overweight and obesity in children can lead to a number of health problems, including heart disease, stroke, type 2 diabetes, and certain types of cancer. To accurately assess the physical development of U5 children, researchers often use BMI. It is a composite measurement computed from anthropometric dimensions like height (length) and weight. It is a widely accepted and standardized indicator of physical development that can be used to track growth patterns and identify children who may be at risk for health problems. By using BMI as a measure of physical development, researchers can better understand the nutritional status of U5 children and identify those who may need additional support to ensure healthy growth and development.

WHO has developed a number of physical development measurement tools that are valid and reliable for use in children of all ages. These tools also include anthropometric measurements (e.g., height, weight, head circumference), physical fitness tests (e.g., strength, endurance, flexibility), and motor skills tests (e.g., running, jumping, throwing).

3.3 The outcome variable

The BMI, in our case has a normal continuous measurement scale and is normally distributed with a mean of 15.318 and a standard deviation of 2.061. Its transformed version also has a normal distribution with different mean and standard deviation, as shown in (AppendixC).

However, applying ordinary statistical methods to the continuous BMI variable and interpreting the results directly may not provide adequate insights for readers and users of the study results. Epidemiologists and public health professionals are interested in information about physical development in terms of categories such as underweight, normal weight, and overweight. There are further categorizations based on different organizations, ranging from severe thinness to morbid obesity.

As depicted in (AppendixF) WHO categorizes children's physical development from severe thinness to morbid obesity, while theCDC and IOTF categorize it from thinness to morbid obesity. These organizations use percentiles in their categorizations.

In this study, we converted the percentiles to corresponding approximate quantities to simplify the results and make them more meaningful in terms of the three commonly used terminologies: underweight (UW), normal weight (NW), and overweight (OW).

According to the WHO's categorization, a BMI below the 5^{th} percentile is considered underweight, a BMI between the 5^{th} and 85^{th} percentile is considered normal weight, and a BMI above the 85^{th} percentile is considered overweight. These quantities correspond to $15.742kg/m^2$ and $17.819kg/m^2$, respectively. We rounded these values up to $16kg/m^2$ and $18kg/m^2$ for simplicity. Therefore, in this study, we will use the following BMI cut-offs to categorize children's physical development: Underweight: BMI < $16kg/m^2$, Normal weight: $16kg/m^2 \leq BMI < 18kg/m^2$ and Overweight: $BMI \geq 18kg/m^2$ (Oliveira et al., 2022). see (AppendixF).

3.4 Independent variables or covarites

- Sex of children, their age categories, residence and other individual level characteristics.
- Breastfeeding status
- Nutritional status of children and mothers
- Maternal and household factors
- Mother's education status
- Family economic status (wealth index)
- Vaccination status of children
- Access to health service: ANC, PNC, delivery service (at home, hospital)

3.4.1 Individual level characteristics: sex, age category in months, Birth place, and related variables

These characteristics may be associated with child physical development and will help us to understand the factors that contribute to healthy growth.

3.4.2 Breast-feeding status: exclusive breast-feeding status during the first six month from birth and its continuity

This factor examines the proportion of live births exclusively breast-fed during the first six months from birth and its continuity.

This information will help us to understand the relationship between breastfeeding and child physical development. In addition to examining the overall proportion of live births exclusively breast-fed during the first six months from birth, we are also interested in studying the association between exclusive breastfeeding and the response variable. To do this, we will include a variable that records information about when the baby was put to breastfeeding and whether the baby was given any food other than breast milk during the first six months from birth. This information will help us to understand the relationship between exclusive breastfeeding practices and child physical development.

3.4.3 Nutritional status of children and mother

This factor is used to examine whether there is a significant difference in physical development among U5 children with different dieting systems(Bhutta et al., 2013; Victora et al., 2021).

3.4.4 Education status of mother

This factor is also one of the major factors to be studied in this research (Grantham-McGregor et al., 2007).

3.4.5 Economic status of the household

This factor examines the significance of the economic status of the household from which the children were born and are being given care (WHO, 2023f; Black et al., 2013).

3.4.6 Vaccination status of children

This factor examines the significance of the vaccination status of the children (WHO, 2023d; Black et al., 2013).

3.4.7 Access to maternity health facilities: ANC, Birth delivery professional assistance and PNC

Using this factor we examines the significance of the maternity health facility on the physical development of children(WHO, 2023e).

3.5 Methodology

This section consists of two main parts: results and interpretation of statistical analysis using descriptive and inferential statistics.

The descriptive part provides a summary of the data using descriptive statistics to describe the study participants by their characteristics. These characteristics include individual level covariates such as: sex, age, family education level, breast-feeding status, nutritional status; HH level covariates like family wealth index EA level covariates like Health facility, cultural view, media access.

Descriptive statistics summarize the data using MCT and MD such as counts (frequencies), means, proportions and standard deviation. For example, in our study, we report the proportion of male and female children included in the study, the percentage of children who were exclusively breastfed and not, and the distribution of breast-feeding duration categorized by months. These descriptive statistics provide a snapshot of the distribution of the study participants among different level of factors and help us to understand the composition of sample.

The inferential part provides statistics that allow us draw conclusions about the population from which a sample was drawn. These statistics include hypothesis testing for variable significance, model adequacy tests, model comparison, and confidence interval of model parameters. The key parameters in this context are log odds β and odds ratio θ, which is the exponential value of $\beta(i.e., \theta = e^{\beta})$. Both values are used interchangeably to interpret the statistical association between the outcome variable and covariates. β represents the extent to which children's BMI in a certain level of a factor is more likely to fall in the next higher category than that of children in the reference level of the factor, expressed in logarithmic values. On the other hand, θ indicates the ratio of odds of BMI being in the next higher category for children in certain level of the factor to the odds of BMI being in the next higher category for those in the the reference level. For instance: if male is reference level of the factor children's sex and female is treatment level, β is the quantity by which the log odds of BMI of female is more likely to be in next higher category than that of male whereas θ is the quantity by which odds of BMI females more likely to be in the next higher category than that of male setting other covariates constant. The value of β can be negative, 0 and positive whereas θ ranges from 0 to ∞.

In the inferential part of our analysis, we discussed results and interpreted the model parameters estimates of the full model that best fit our data and for which model assumptions met. We made inferences about the entire population from which our sample was drawn. We also discussed the assumptions of the ordinal regression model (proportional odds assumption) and diagnosed whether these assumptions were met or not. We assessed the goodness of fit of the model and examined the distribution of residuals. These diagnostic procedures helped us to ensure that the model was appropriate for our data and that the results were reliable.

Categorical data are commonly encountered in health and behavioral sciences, necessitating statistical methods for modelling and analysis to uncover the existence, nature, direction, and strength of associations between variables. The analysis of categorical data varies depending on the nature of the outcome variable, such as count data, binary, nominal multi-category, or ordinal multi-category.

Most categorical data analysis methods comprise three key components:

1. Random component: Specifies the response variable.
2. Systematic component: Specifies the explanatory variables.
3. Link function: Connects the systematic component with the parameters of analysis (expected values of the random component).

Modeling methods differ based on these components, particularly the nature of the random component. Employing classical modeling techniques for hierarchical data can result in underestimated standard errors and inflated statistical significance, potentially leading to exaggerated conclusions regarding the association between the dependent variable and predictors (as noted by (Austin et al., 2021)). Common link functions include logit and log-linear. Logit is used to model the probability rather than values of variables. For instance, probability of success in binary variables, while log-linear is log of average of variables for count responses (Agresti, 2000).

Categorical data analysis methods, such as GLMs, are viable alternatives to statistical methods when the assumptions of the linear regression model are not met. When some of the underlying assumptions required for ordinary linear regression fail, GLMs become the appropriate method for modeling the data.

GLMs are particularly useful when the normality assumption is violated. When the response variable follows a binomial distribution rather than a normal distribution, logistic regression models become the preferred statistical method of analysis. If the response variable has more than two categories, proportional odds regression which can be named as cumulative logistic regression is employed for ordinal responses. These methods are used to investigate the effects of covariates on patterns of probability of response being in one of C categories. The association between variables is measured using logit (log odds) and log-linear functions.

When GLMs are not suitable for the scenario under study, GLMMs become the most appropriate method to employed. GLMMs are utilized in various scenarios and considerations. A common consideration for applying GLMMs is when there is correlation between responses within clusters existing in the sampling design hierarchy. If the independence assumption of the response variable is violated in addition to non-normality, GLMMs, which take the sampling design effect into account, become the appropriate method to model the data.

GLMMs are also known as random effect models, multilevel models, or hierarchical linear models. These models are suitable when individuals in the sample are dependent, and the response variable is non-normally distributed. The distribution of the response variable in GLMMs belongs to the exponential family (Agresti, 2000; Hedeker, 1994; Sommet and Morselli, 2017).

Categorical data analysis methods are employed to fit and interpret regression models for responses with ordered categories. These methods enable researchers to minimize information loss during analysis (Salini and Kenett, 2011). Ordinal logistic regression is a statistical method that deals with response variables with response membership among one of C mutually exclusive possible categories. The probabilities of these categories are constrained such that $P_1 + P_2 + ... + P_C = 1$.

Cumulative probability models are preferred for ordered categories of such group membership (De Onis and Branca, 2016). Additionally, it is common in research to utilize the concept of threshold values. This assumes that ordered responses are extended and created from some latent continuous variable such that $Y = y_c$ if and only if $\gamma_{c-1} \leq Y_l < \gamma_c$, where Y_l is the latent continuous variable from which the ordered variable was generated. This means that the value of the ordered variable will be in category C if and only if the value of the latent (unobserved) continuous variable is at least γ_{c-1} and less than γ_c.

For example, consider the BMI of children. The BMI will be in the under-weight category if and only if the continuous BMI is at least γ_0 and less than $16Kg/m^2$. It will be in the normal weight category if it is at least $16Kg/m^2$ and less than $18Kg/m^2$. Finally, it will be in the over-weight category if it is at least $18Kg/m^2$ and γ_c. In this case, γ_0 is 0 and γ_c is ∞. Using this example, a child with a BMI of 0.00 - 15.99 are under-weight, a child with a BMI of 16.00 - 17.99 are normal weight, and a child with a BMI of 18.00 - ∞ are over-weight (Jekel, 2007).

The equation (3.5.1) below represents the mathematical forms the functional relationship between log-odds of BMI of child i fail in one category rather than the other the complementary categories given the values of explanatory variables. α is the log of probability of getting values of BMI in certain category rather than other left categories given values of explanatory variables are 0. In other words, α is the intercept of the logit model, which represents the log-odds of the outcome when all the explanatory variables are set to 0. β_P 's are the amount by which log of probability of getting BMI in certain category rather than other left categories increases or decreases due to X_P explanatory variable.

The the equation is the multiple logistic regression model applied under the assumption of independence between response and/or individual in the study. It extends ordinary regression model when normality assumption not met; when the response variable is exponential family (Binomial distribution). It quantifies the association between covariates and response variable through log-odds, onditional on other covariates. β_j is the measure of effect of X_j on Y. π_i is the probability i^{th} individual has response in success category. This quantity is differ depending on values of covariates. For instance, it differs among breastfed and baby formula-fed infants when the response observed in whether the child's BMI is happen is over-weight or not (Belina, 2008).

$$logit(\pi_i) = \alpha + \beta_1 X_{i1} + \beta_2 X_{i2} + ... + \beta_p X_{ip}; i = 1, 2, \dots n. \quad (3.5.1)$$

This equation is the simplest version of logistic regression model popular to fit logit model for response variable with binary response. For example the log-odds of being above median value and below it. α represents the log of probability of BMI being above median value rather than below it given values of X's 0. β_P 's represent the amount by which the log of probability of BMI being in above median value rather than below it at given some values of X_P. This equation also set to measure the odds ratio to assess the effect of categorical explanatory variable. For instance to measure the effect of exclusive breast-feeding on getting obesity, we set exclusive breast-feeding as "yes" or "no", if β corresponding to the explanatory variable (EBF) is 0.75, it means that the log of probability of getting obesity is 0.25% less for yes category than no category. This 0.75 is called odds ratio (θ). It tells that the ratio of the probability of getting obesity in Exclusive breast-fed children is less than the probability of getting obesity for Not exclusively breast-fed children. If the quantity is 1, it means that EBF has no statistically significant effect on BMI, and if the quantity is greater than 1, it means that the probability of getting obesity in exclusively breast-fed children is greater than that of not exclusively breast-fed children setting baby formula-fed as reference group. Since we said about the basics of logistic regression model when assumption of independence is met, we go for an extension of logistic regression model when the assumptions of logistic regression models not met.

3.5.1 Generalized Linear Mixed Model (GLMM)

The choice of data analysis and modeling methods depends heavily on the data generating process employed (Aggarwal and Aggarwal, 2017; Agresti, 2000). Survey data collected using multi-stage sampling designs requires distinct statistical methods compared to unit-level sampling designs. In multi-stage sampling, measurements from subjects within the same cluster tend to be correlated, while measurements between different clusters are less correlated. Therefore, appropriate methods are needed to account for this variation at all levels, ensuring accurate analysis procedures.

As explained by (Heck and Thomas, 2020; Hox and McNeish, 2020) GLMM extends the GLM by incorporating both fixed and random effects. This allows researchers to simultaneously model the effects of covariates while accounting for dependencies among responses due to sampling design. The random component estimated using GLMM is often referred to as the sampling design effect.

In our study, we employed GLMM because the data we analyzed came from the DHS, which is a multilevel survey dataset. Hierarchical modeling techniques, such as GLMM, are well-suited for analyzing multilevel data, as they can capture the nested structure of the data and account for dependencies within and between different levels of the sampling design.

Equation (3.5.2) represents LMM for handling the effect of explanatory variables on children's BMI, assuming a continuous and normally distributed response variable. However, if BMI is categorized as under-weight, normal-weight, and over-weight, a different model is needed so as to take into account the non-normality and dependence among study participant. In cases where children's BMI measurements within the same household (HH) and enumeration area (EA) are more correlated to each other than measurements from different HHs and EAs, GLMM is an appropriate choice. It enables handle non-normality and dependence and hierarchical structure of the data, where children are nested within HHs and EAs.

According to (Sommet and Morselli, 2017; Hedeker, 2016) parameters in that the model made up are fixed and random intercepts and slopes. Fixed intercepts the overall average value o BMI at 0 values of explanatory variables. Level two random intercept is the distance of the average values of BMI from fixed intercept. In similar way the distance of average values of BMI in level three from fixed effect is random intercept of level three. The same logic works for fixed and random slopes.

$$Y_{j(i)k} = X_{j(i)k}^{T}\beta + v_{j(i)} + u_i + \epsilon_{j(i)k} \tag{3.5.2}$$

where: $Y_{j(i)k}$ is BMI of k^{th} child in j^{th} HH and i^{th} EA;

it runs from 1 to n; $n = \sum_{i=1}^{305}\sum_{J=1}^{n_i}\sum_{k=1}^{n_{j(i)}} n_{j(i)k}$, β is $px1$ vector of unknown parameters, $X_{j(i)k}$ is $px1$ vector of level one of covariance, $v_{j(i)}$ is variation component due to level two (HH), u_i is variation component due to level three (EA), ϵ_{ijk} is over all error term.

Important point needed to be noted here is the proportional odds assumption of ordinal regression model. It states that the effect of covariates is the same in each category of response variable. That is β 's are equal for each category; that is why β in the equation (3.5.2) above has no subscript.

However, treating BMI as a continuous variable and interpreting the results accordingly may not provide meaningful information for readers and users of the study, especially for health professionals and community members. Therefore, categorizing BMI into under-weight, normal, and over-weight based on WHO developed criteria is more appropriate in this context. This categorization results in an ordinal multi-category response variable with three ordered categories.

Since BMI was made an ordinal variable, linear regression models are no longer suitable. Instead, a more appropriate statistical method is the Multilevel Ordinal Logistic Regression model. This model can handle ordinal response variables and account for the hierarchical structure of the data, where children are nested within households and enumeration areas.

Multi-level modeling, also known as hierarchical linear modeling or mixed-effects modeling, is a statistical technique that accounts for the nested structure of data. It is used when observations are grouped or clustered together, and the researcher is interested in understanding the effects of both individual-level (within-group) and group-level (between-group) variables on the outcome of interest.

Multi-level modeling allows researchers to investigate how both individual-level and group-level characteristics jointly influence the outcome variable(s) of interest. It is a powerful tool for analyzing data that has a nested or hierarchical structure, such as students within schools or employees within companies. Multi-level modeling can provide valuable insights into the relationships between individual-level and group-level variables and the outcome variables.

However, it is important to note that multi-level modeling is a complex technique. It is important to have a good understanding of the data and the research question before using it. When interpreting the results of a multilevel model, it is important to consider the effects at both the individual-level and the group-level. see (3.5.3) below.

$$P(Y_{j(i)k_c} \leq c) = \frac{exp(X^T_{j(i)k}\beta + v_{j(i)} + u_i)}{(1 + exp(X^T_{j(i)k}\beta + v_{j(i)} + u_i)} \tag{3.5.3}$$

where: $Y_{i(j)k}$ is BMI score of k^{th} child in j^{th} HH and i^{th} EA, u_i is variation due to i^{th} EA or random factor at highest (third) level, $X_{i(j)k}$ is vector of values of explanatory variable for k^{th} child in j^{th} HH and i^{th} EA, $Z_{i(j)}$ is vector of random factors at second level and logit is the link function for the model.

The model described by equation (3.5.3) can be expanded to predict the probability of the response occurring within category C and then transformed by taking the logarithm. This transformation eliminates further discussion regarding probability, focusing solely on the natural logarithm of the probability. Here the number of parameters in this equation is the same as in equation (3.5.2). The distinction lies in the interpretation of the parameter, which now represents the log odds of BMI falling within category "C" or lower, as opposed to above category "C," unlike the previous equation that considered the average BMI.

Specifically, in a mixed-effects ordinal logistic regression model with a three-level ordinal response variable with three ordered categories, the model can be represented by in equation (A.0.1) in AppendixA. The model consists of both fixed and random effects components, with predictor variables at only lower and higher level assuming level-two is insignificant and negligible. The equation represents the probability that BMI falls in one of three regions: less than the first threshold value, between the first and second threshold values, or greater than or equal to the second threshold value. The coefficients in the equation are the same across the three models, but the intercepts vary. This assumption should be diagnosed to check the model fit.

The model also includes variance-covariance matrices for the random effects $\mathbf{b}_i$ and the residuals The case when both random effects of level two and level three are significant is represented as expressed by equation (A.0.2) in AppendixA, (3.5.4) alternatively.

3.5.2 Multi-level Ordinal Logistic regression model

The model represented in Equation (A.0.1) assumes that the variation at level two (e.g., households) is negligible compared to the variation at level one (e.g., children) and level three (e.g., enumeration areas). In contrast, the model represented in Equation (A.0.2) assumes that all levels of variation are significant and important.

A more general and comprehensive form of the model is represented in Equation (3.5.4). This model includes random effects at all three levels, allowing for the investigation of the effects of both individual-level, household-level, and enumeration area-level variables on the outcome variable.

Multi-level Ordinal Logistic Regression (OLR) model is the statistical method we selected for our study because it is appropriate for analyzing the data we used. As discussed earlier, the response variable in our data has three ordered categories, and the data was collected using a multilevel sampling design that introduces both random and fixed effects. Factors influencing the response variable are present at both the cluster level (enumeration area) and the individual level (children).

To account for the hierarchical structure of the data and the mixed effects, we fitted a three-level OLR model. Equation (3.5.4) represents the model, which incorporates both fixed and random effects that contribute to the variation in BMI among children within households and enumeration areas. β is a vector of fixed effect parameters, u_i represents the variation due to enumeration area-level random factors, and $v_{j(i)}$ represents the variation in BMI due to household-level random factors.

$$\begin{aligned} P(Y_{j(i)k} \leq c) &= \frac{exp(X^T_{j(i)k}\beta + Z^T_{i(j)}v_{j(i)} + W^T_i u_i)}{1 + exp(X^T_{j(i)k}\beta + Z^T_{i(j)}v_{j(i)} + W^T_i u_i)} \\ \implies logit(Y_{j(i)k} \leq c) &= \gamma_c - X^T_{j(j)k}\beta + Z^T_{i(j)}v_{j(i)} + W^T_i u_i \end{aligned} \tag{3.5.4}$$

Ordinal logistic regression assumption (parallel line assumption)

The proportional odds model assumption, also known as the ordered logit model or proportional odds regression, is used for analyzing ordinal dependent variables.

It extends the concept of logistic regression (which deals with dichotomous dependent variables) to handle more than two ordered response categories. For instance, suppose the response variable we are studying has five possible outcomes: "poor," "fair," "good," “very good,” and “excellent.” The model assumes that the probabilities of these outcomes are functions of some independent variable(s) X (Williams, 2006). For a fixed value of X, the logarithms of the odds (not the probabilities) of answering in certain ways are calculated. The proportional odds assumption states that the differences between these logarithms to get the next category are the same regardless of X. In other words, the difference in the logarithm of the odds of having “poor” or “fair” health minus the logarithm of having “poor” health is the same regardless of X. Similarly, this holds for other adjacent categories(Liu et al., 2023). Implications: The proportional odds assumption is crucial for the model to be valid. If the assumption is met, the model estimates the effects of predictors consistently across all thresholds. If the assumption is violated, alternative models (such as the partial proportional odds model) may be more appropriate.

3.5.3 Contextual meaning of Fixed Effects, random effects, Variance components

Fixed effect is the relationships between the 3factors and the response variables at the individual level. In our case individual level predictors like: effects of educational level of mothers, awareness and attitude towards breast-feeding practice, health condition of mothers and related factors on physical development of children. On the other hand random Effects capture the variability between groups (EAs and HH in our case) and that cannot be explained by the fixed effects. They help to quantify the impact of group-level factors on physical development of children. These indicate the amount of variation in the dependent variable that is attributable to the different levels in the model (e.g., within-group variation and between-group variation). This captures the proportion of variability at EA level and HH level from total variability.

ICC measures the amount of total variance that can be attributed to variations between clusters. It ranges from 0 to 1 and provides insights into the importance of group-level effects. Significance and Confidence Intervals: Assess the significance of coefficients and their associated confidence intervals to determine the strength and precision of the estimated effects. To analyze the impacts of breastfeeding and related factors on the physical development of under-five children, a multilevel modeling approach will be employed. This method allows for the consideration of the hierarchical nature of the data, with children nested within households or communities.

3.6 Intra-class correlation coefficient (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 the proportion of unexplained variance that is at the cluster level, and is given by:

$$
\begin{aligned}
ICC_{bi} &= \frac{\sigma^2_{bi}}{\sigma^2_{bi} + \sigma^2_{bj(i)} + \sigma^2_{bj(i)k}} \\
ICC_{bj(i)} &= \frac{\sigma^2_{bj(i)}}{\sigma^2_{bi} + \sigma^2_{bj(i)} + \sigma^2_{bj(i)k}} \\
ICC_{bj(i)k} &= \frac{\sigma^2_{bj(i)k}}{\sigma^2_{bi} + \sigma^2_{bj(i)} + \sigma^2_{bj(i)k}}
\end{aligned} \tag{3.6.1}
$$

where σ^2_{bi} is the cluster (level 3) (EA) variance component, and $\sigma^2_{bj(i)}$ is the level 2 (household) variance component and $\sigma^2_{bj(i)k}$ is level one variance component. 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 $\frac{\pi^2}{3} \approx 3.29$ Agresti (2000); Ejigu et al. (2018); Hedeker (1994); Sommet and Morselli (2017).

3.7 Model Parameter Estimation methods

The parameters to be estimated in the mixed-effects ordinal logistic regression model include:

- Fixed effects parameters: $\alpha_1, \alpha_2, \alpha_3, \beta_1$.
- Random effects parameters: Variance-covariance matrices for the level-three and level two random effects $u_{j(i)}$ and u_i

These parameters are typically estimated using RMLE or MMLE and other extension of MLE which are more robust and appropriate methods, considering the hierarchical structure of the data. For a multi-level ordinal logistic regression model where the response variable is nested within multiple levels of grouping the likelihood function becomes more complex than usual MLE due to the hierarchical structure of the data. The likelihood function for the multi-level ordinal logistic regression model can be expressed as the product of the conditional probabilities of observing the responses within each cluster and group.

The extension of MLE to considered to take into account the hierarchical nature of the data to reduce information loss during the estimation are, Marginal Maximum Likelihood estimation (MMLE) or Restricted Maximum Likelihood Estimation (REMLE) can be used to estimate parameters in multilevel ordinal logistic regression model (Hedeker, 1994).

By extending the model given equation (A.0.2) for $c \geq 3$ category, it can be expressed as equation 3.7 below.

$$logit(p_{j(i)kc}) = \alpha_{ci} + \alpha_{cj(i)} + \beta_1 X_{j(i)k} + b_{j(i)k}$$

The likelihood function for the three-level mixed effects model would involve integrating over all levels of nesting, accounting for the variability at each level. To estimate the parameters of the model, you would maximize this likelihood function with respect to the fixed effect coefficients β_1, the cluster-specific intercepts $\alpha_{0k}, \alpha_{1k}, \alpha_{2k}$ the group-specific intercepts $\alpha_{0j(i)}, \alpha_{1j(i)}, \alpha_{2j(i)}$ and the variance of the random effects σ_b^2 at each level of nesting.

The likelihood function can be written as:

$$L(\beta, \alpha_{0i}, \alpha_{1i}, \alpha_{2i}, \alpha_{0j(i)}, \alpha_{1j(i)}, \alpha_{2j(i)}, b_{j(i)k}) = \prod_{i=1}^{N} \prod_{j=1}^{n_i} \prod_{k=1}^{n_{j(i)}} P(Y_{j(i)k} | X_{j(i)k}) \tag{3.7.1}$$

where: $P(Y_{j(i)k} | X_{j(i)k})$ is the probability that BMI being in certain category given values of all explanatory variables as given in equation (3.5.3) and more generally it is given by equation (3.5.4), $N$is the total number of $EA = 305$, j is the total number of HH within each EA, K is the total number of individuals within each HH and EA, Y is the Vector of observed response variables, X is the matrix of predictor variables and α and β are the parameters to be estimated.

3.8 Diagnosis and Specification

The primary outcome variable, such as BMI or height-for-age z-score, were regressed on breast-feeding duration and other relevant factors at the individual level. Additionally, household and community-level variables were included to account for broader contextual influences. In this model, the level at which response nested in the cluster is explained using the specification. (Liu et al. (2023); Victora et al. (2016))

The equation used the model that takes into account the design effect of data generating mechanism. This means data for BMI value of children obtained by measuring children that nested in HH; where as HH nested in the cluster Enumeration area in our case. Applying ordinary regression model for data generated using such a sampling design leads to underestimate standard error. This impact the test statistics larger and increase probability of type one error. Finally, it results in wrong conclusion and make the endeavor of researchers useless. Therefore, employing an appropriate method that takes into account the sampling design, measurement and collection mechanism that enables to quantify as much all-possible sources of variation as possible is of main attention of analysis.

3.9 Model Selection criteria

AIC and related statistical criteria for model selection that balance the fit and complexity of a statistical model were used. The tools are based on the likelihood function, which measures how well the model explains the observed data

$$AIC = -2\log(L) + 2k \tag{3.9.1}$$

where L is the maximized value of the likelihood function, and k is the number of parameters in the model and n is the number of observations in the data.

3.9.1 Model Adequacy

The study used likelihood ratio test to evaluate the model fit adequacy. The test is the ratio of two fitted models and the test statistics ranges from 0 to 1. 0 value of LRT implies that the restricted model is less likely to generate the data than the unrestricted model. The value of LRT test statistic 1 means that perfect fit of the model. The test reject the hypothesis of adequacy of model and support the goodness of it. LRT test statistic is computed using the equation 3.9.2. Smaller value of LRT shows inadequate model fit and reject the hypothesis of adequacy of the model.

$$\Lambda = -2(log(L_0) - log(L_1)) \tag{3.9.2}$$

where: L_0 is the likelihood of the simpler model and L_1 is the likelihood of the more complex model.

Under the null hypothesis that the simpler model is true, the test statistic Λ follows a chi-squared distribution with degrees of freedom equal to the difference in the number of parameters between the two models. For a mixed effects ordinal logistic regression model, the number of parameters in the simpler model would typically be fewer than that in the more complex model due to the inclusion of additional random effects. $\Lambda \sim X^2(df); df = p_1 - p_0$; where p_1 and p_0 are number parameters of unrestricted and restricted models respectively.

The likelihood ratio test is commonly used in model comparison to assess whether the inclusion of random effects improves the overall fit of the mixed effects ordinal logistic regression model. To perform the likelihood ratio test, you would compare the value of Λ to the critical value of the chi-squared distribution with the appropriate degrees of freedom at a chosen significance level. If the test statistic exceeds the critical value, you would reject the null hypothesis and conclude that the more complex model provides a significantly better fit to the data.

Chapter 4

Results

This chapter consists of: descriptive statistical analysis results, inferential statistical analysis, hypothesis tests results, interpretation of the results.

4.1 Descriptive statistics

A total sample of 4,825 U5 children were included in the study. The distribution of children across households (HH) was as follows: 1,895 HH had one U5 child each while a small number of HHs (9 HHs) had five U5 children.

In urban areas, the prevalence of UW, NW, and OW is 42.34%, 39.51%, and 18.15%, respectively. In rural areas, the prevalence of UW, NW, and OW is 48.24%, 33.76%, and 18%, respectively. This was also presented using the Figure 4.1 below. The Figure shows that prevalence of UW is larger for rural resident than urban residents and prevalence of normal weight is larger for urban than rural. Over-weight is almost the same for both urban and rural with slightly larger for urban residents.

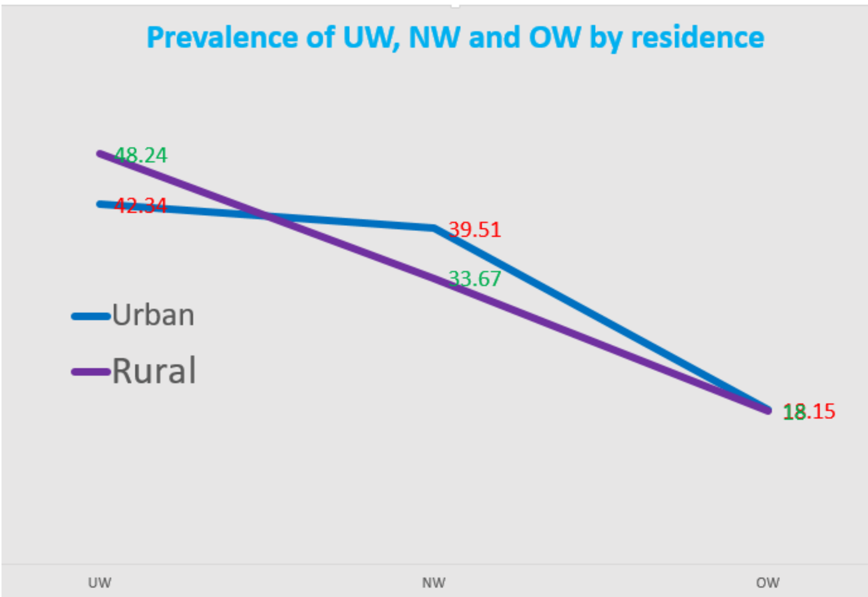


Figure 4.1: The prevalence of UW, NW and OW by urban and rural residence

Table 4.1 below shows that among 4,825 U5 children observed during the data collection and whose height and weight were measured, 2,543 (52.68%) were under-weight, 1,676 (34.72%) were normal, and 606 (12.60%) were over-weight. Approximately 12.60% of Ethiopian children are over-weight, which may increase their risk of obesity and related diseases in adolescence and adulthood age. In Ethiopia, only 34.72% of children have normal physical growth. The confidence interval for true value of population proportion is (51.27 , 54.90), (33.39 , 36.08) and (11.69 , 13.56) for UW, NW and OW respectively.

Table 4.1: Proportion of Underweight, Normal weight and Over-weight among study participants

Category	Number of children	percentage (95% Confidence interval)
Under-weight	2,543	52.68 (51.27 , 54.90)
Normal weight	1,676	34.72 (33.39 , 36.08)
Over-weight	608	12.60 (11.69 , 13.56)
Total	***4,825***	

Figure 4.2 below presents the percentage distribution of UW, NW and OW of U5 children in Ethiopia. It presents the result described in Table 4.1 above using graph.

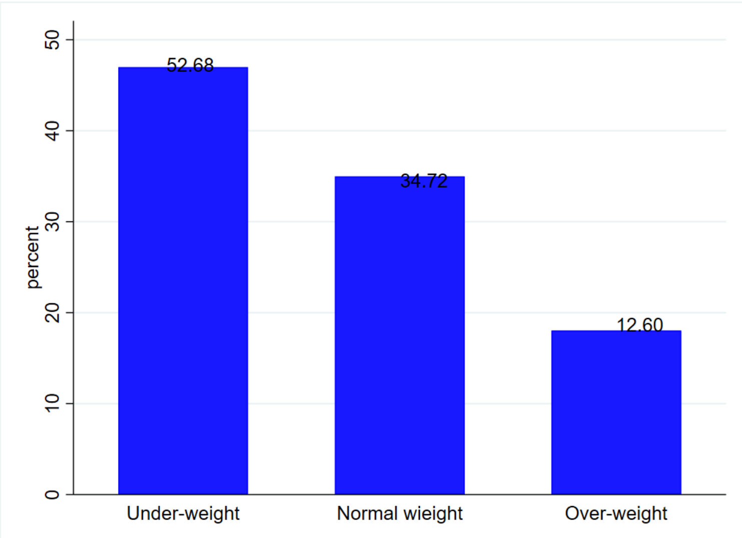
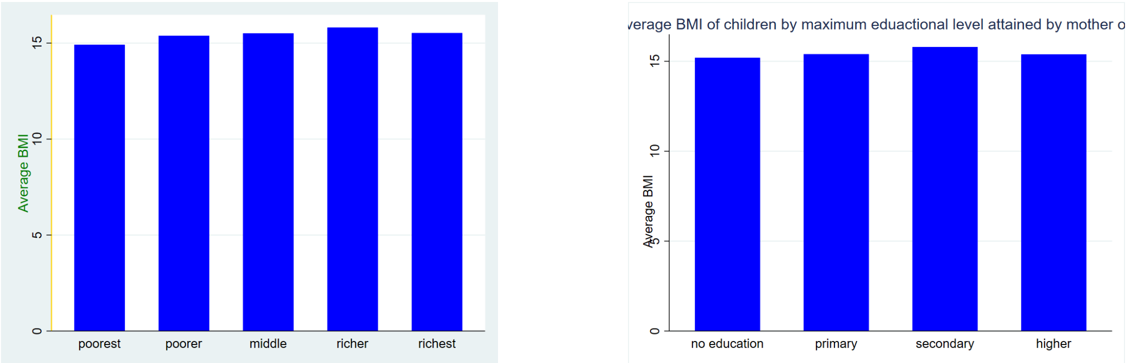


Figure 4.2: Percentage distribution of children weight.

The Figure 4.3a and 4.3b below presents the average BMI of children classified by some covariates. Figure 4.3a shows that the ABMI of children from poorest, poorer, middle, richer and richest families is 14.911, 15.386, 15.512, 15.811 and 15.523 respectively. Figure 4.3b shows that the ABMI of children whose mothers attained no education, primary education, secondary education and higher is 15.240, 15.497, 15.799 and 15.665 respectively.

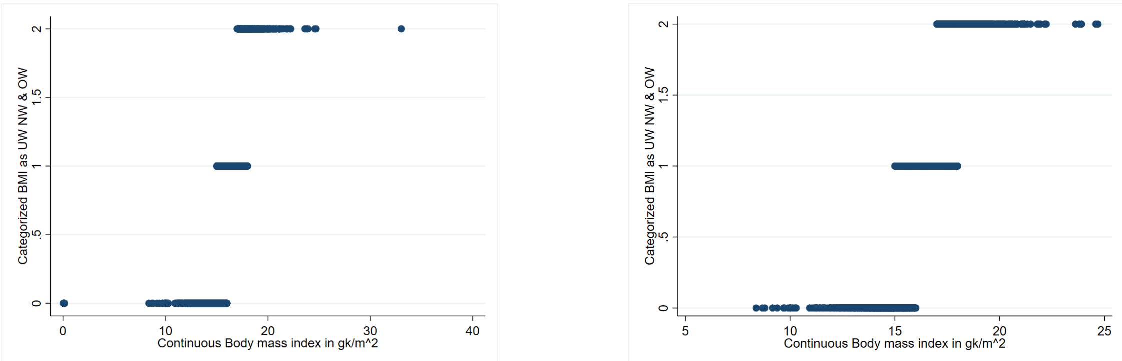
Figures 4.4a and 4.4b illustrate the body mass index (BMI) values of children and their corresponding weight categories. Figure 4.4a includes outlying values, while Figure 4.4b excludes them. It presents that Children fall under UW if their BMI is approximately less than $16.00 kg/m^2$, normal weight if their BMI ranges from $16.00 kg/m^2$ to $18.00 kg/m^2$, and OW if their BMI 18.00 or above. It is also possible to see that the BMI of children accumulated from $8.50 kg/m^2$ to $24.00 kg/m^2$. The maximum BMI value in the figure



(a) Average BMI classified by Economics status of parents (b) Average BMI classified by maximum education mother attained

Figure 4.3: Average BMI classified by some individual and HH level characteristics

is $33.00 kg/m^2$. Further the graph shows that BMI ranges from $0 - 33 kg/m^2$. This extreme values (outlying values) my be as a result of measurement error and hence we excluded from the model due to insistence with BMI range set by WHO (Oliveira et al., 2022; Racette et al., 2017).



(a) With outliers (b) After outliers removed

Figure 4.4: Range of BMI category

Table 4.2 presents the composition of the target population under study. It provides descriptive statistics of the total number of children (study participants) related to various potential risk factors associated with children's physical and cognitive development. These factors include those related to children and their parents and community they live with. The Table includes information on child sex, age categories, parents' residence, breastfeeding status, vaccination history, prenatal care status, birth delivery assistance, parents' wealth index, sanitation facility, nutrition status, media access, parents educational status and other factors.

Of the 4,825 children eligible for height and weight measurement during the survey: 24.59%, 21.28%, 21.77%, 18.23% and 12.35% are between 0-12, 13-24, 25-36, 37-48 and 49-59 months old respectively. Of the total number of children, 35.87% (1,743 children) have received complete vaccination, 44.52% (2,163 children) and 16.05% (780 children) were has not been vaccinated at all.

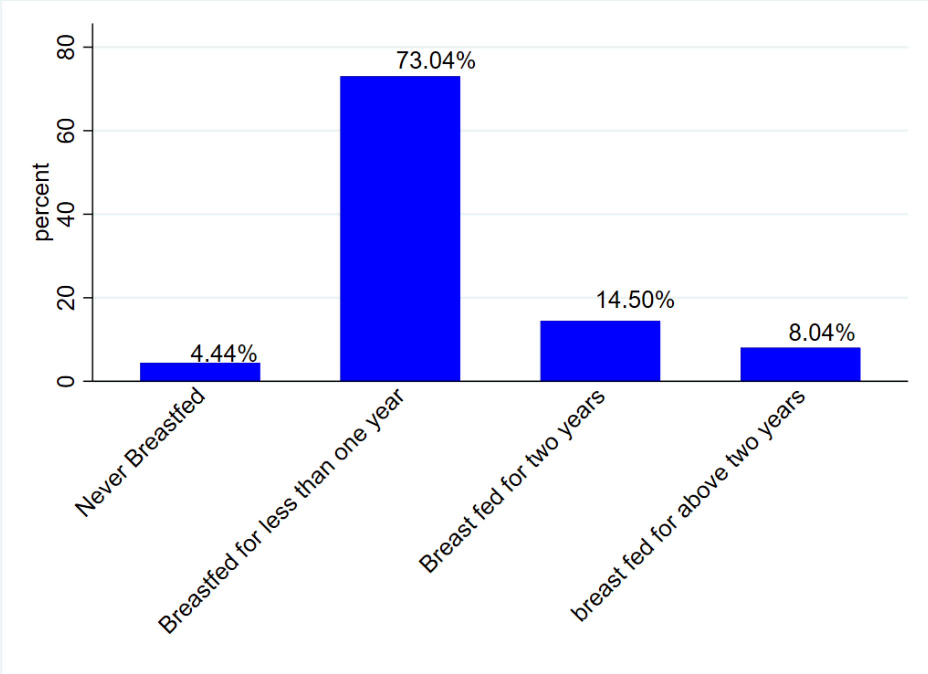


Figure 4.5: Breast-feeding status among study participant

The proportion of breast-feeding among children in the study is presented in Figure 4.5. It shows that 4.44% (215 children) were never breastfed at all, 73.04% (3,522 children) are breastfed for at most one year, 14.50% (700 children) are breastfed for at most two years, and 8.04% (388 children) are breastfed for more than two years.

Table 4.2 shows that the average BMI of children who were never breastfed is 15.02 kg/m2, which is 0.30 kg/m2 higher than the overall average BMI. Children who were breastfed for less than one year have an average BMI of 15.27 kg/m2, which is 0.05 kg/m2 higher than the overall average BMI. Children who were breastfed for at most two years have an average BMI of 15.66 kg/m2, which is 0.03 kg/m2 higher than the overall average BMI. Children who were breastfed for more than two years have an average BMI of 15.29 kg/m2, which is 0.01 kg/m2 higher than the overall average BMI.

Table 4.2: Summary of descriptive statistics

Explanatory variables (Factors)	Percentage (number of children)	Average BMI in Kg/m^2
Child Sex		
Female	50.92% (2,457)	15.33
Male	49.08% (2,368)	15.48
Age category in Months		
(0-12)	24.59% (1,203)	15.81
(13-24)	21.28% (1,044)	15.58

Continuation of Table 4.2		
Explanatory variables (Factors)	Percentage (number of children)	Average BMI Kg/m^2
(25-36)	21.77% (1,067)	15.28
(37-48)	18.23% (897)	14.94
(49-59)	12.35% (614)	14.53
Parents Residence		
Urban	22.58% (1,089)	15.419
Rural	77.42 (3,736)	15.291
Exclusive feeding status		
Exclusive Breast-fed	46% (2,220)	15.29
Not Exclusive breast-fed	54% (2,605)	15.60
When Breastfeeding established		
Immediately	73.54% (3,548)	15.636
Later after delivery	26.46% (1,277)	15.026
Vaccination history of child		
Never vaccinated	16.05% (774)	15.232
Partially vaccinated	44.52% (2,148)	15.726
Completely Vaccinated	35.87 (1,903)	14.826
Antenatal care status		
No Antenatal care	17.84% (861)	15.385
Got Antenatal care	82.16% (3,964)	15.310
Birth Delivery assistance status		
No professional assistance	49.72% (2,399)	15.158
Got Professional assistance	50.28% (2,426)	15.498
Post natal care status		
No PNC	7.56% (365)	15.776
Partial PNC	88(4246)	15.329
Complete PNC	4.40% (214)	15.900
Breastfeeding Length in Months		
Never Breastfed	4.44% (215)	15.020
Breastfed for one year and less	73.04% (3,522)	15.271
Breastfed for two years	14.50% (700)	15.660
Breastfed for more than two years	8.04% (388)	15.290
Parents Wealth index		
Poorest	35.01% (1,689)	14.911
Poor	18.07% (872)	15.386
Middle	14.67% (708)	15.512

Continuation of Table 4.2		
Explanatory variables (Factors)	Percentage (number of children)	Average BMI Kg/m^2
Rich	12.52% (604)	15.811
Richest	19.73% (952)	15.523
Education mothers attained		
No education	54.94% (2,651)	15.240
Primary	32.01% (1,544)	15.497
Secondary	7.96% (384)	15.799
Higher	5.09% (246)	15.665
Nutritional Status		
Incomplete Nutrition	14.8% (714)	15.324
Partially complete Nutrition	84% (4053)	15.330
Complete nutrition	0.12% (58)	15.710
Total Number of Children	***4,825***	

In general, the composition of study participants, the average BMI classified by characteristics are presented in Table 4.2. It has been shown that the average BMI of children varies with: sex, age, residence, breast-feeding status, vaccination history, ANC, birth delivery professional assistance, breast-feeding length, parents' wealth index, and others covariates.

ABMI is 15.33 kg/m^2 for female children and 15.48 kg/m^2 for male. Children in the youngest age category 15.81 kg/m^2), while children in the oldest age category (49-59 months) have ABMI 14.53 kg/m^2. Children living in urban areas have ABMI 15.419 kg/m^2 and those living in rural areas 15.291 kg/m^2.

Children who are start breastfeeding immediately after delivery have ABMI 15.636 kg/m^2 and those who are breastfed later after delivery have 15.026 kg/m^2. Children who are exclusively breastfed have ABMI 15.29 kg/m^2 and those who are not exclusively breastfed have 15.60 kg/m^2. The ABMI of children who are never breastfed, breastfed for one year, breastfed for two years, and breastfed for more than two years is 15.020 kg/m^2, 15.270kg/m^2, 15.660kg/m^2 and 15.290kg/m^2 respectively. Children who are never vaccinated, partially vaccinated and completely vaccinated have ABMI 15.232kg/m^2, 15.726 kg/m^2 and 14.826 kg/m^2 respectively). Children whose mothers received ANC have ABMI 15.310 kg/m^2 and those whose mothers did not have 15.385 kg/m^2. Children who were delivered with professional assistance have ABMI 15.498 kg/m^2 and 15.158 kg/m^2. Children whose mothers received no PNC at all, partial PNC and complete PNC have ABMI 15.776kg/m^2, 15.329kg/m^2 and 15.900kg/m^2 respectively.

4.2 Inferential Statistics

4.2.1 Significance of level 2 and level 3 variation (Null model)

The Table 4.3, presents the results of a multilevel ordinal logistic regression model when all predictors are fixed at zero. The model estimates the variance components for the random effects at all levels and provides the coefficients and p-values for the significance of the hierarchical nature of the data. The 95% Confidence interval for true population variation at all levels is also presented in the table.

The higher level, level 3 (EA)'s variance component (0.290) represents the variation in the outcome variable that is attributed to differences between level 3 units (EAs) after accounting for the fixed effects. This suggests that there is substantial variation in the outcome variable across EAs. Level 2 (HH)'s variance component (0.060) represents the variation in the outcome variable that is attributed to differences between level 2 units (HHs) after accounting for the fixed effects and level 3 variation. This variance component is smaller than that of level 3, indicating that a smaller proportion of the variation in the outcome variable is explained by differences between HHs. The variance of the standard logistic model is $(\pi^2)/3 \approx 3.29$. Using these quantities, we can calculate the intraclass correlation (ICC) for each level. The ICC represents the proportion of variance in the model that is attributable to a specific level of the hierarchy.

The hierarchical nature of the data introduces random and fixed variation in body mass index (BMI). The variation contributed by the highest level (EA) contributes significantly to variation in BMI, and the variation contributed by the intermediate level (HH) is also significant.

The ICC for the enumeration area is calculated as follows:
$ICC(EA) = \frac{Var(EA)}{(Var(EA)+(HH)+var(BMI))}$.
$ICC(EA) = \frac{0.290}{(0.290+0.06+3.29)} = \frac{0.290}{3.64} \approx 8\%$. This result indicates that the enumeration area contributes approximately 8% to the total variation in BMI. Similarly, the ICC for the household is calculated as follows:
$ICC(HH) = \frac{var(HH)}{(Var(EA)+Var(HH)+var(BMI)}$.
$ICC(HH) = \frac{0.06}{(0.290+0.06+3.29))} \approx 3\%$.

This result indicates that the household contributes approximately 3%. The left 89% of total variation BMI is the contribution of explanatory variable. As a result, the hierarchical nature of the data introduces random and fixed variation in BMI. The enumeration area and household levels variation contribute approximately about $11\%(8\% + 3\%)$. Based on the intra-class correlation (ICC) results, we can decide that the hierarchical nature of the data is important to consider in the statistical modelling. The most appropriate model for handling such a scenario is a three-level ordinal logistic regression model, which takes into account the clustering of individuals within HH and HH within EA.

By using a three-level ordinal logistic regression model, we can obtain more accurate estimates and make more reliable inferences about the relationship between BMI and the explanatory variables in the model.

Table 4.3: Multi-level ordinal logistic regression model setting with all predictors zero (the null model)

Variation	Coefficient	*sig.* (95% Confidence interval)
γ_1	0.294	*** (0.184 , 0.403)
γ_2	1.394	*** (1.251 , 1.537)
Level 3 (EA) var(constant)	0.290	*** (0.270 , 0.473)
Level 2 (HH)	0.06	* (0.00 , 0.11)
Level 1 (fixed effects)	$\pi^2/3 \approx 3.29$	
Total	***4,825***	
Note: *** p-value < 0.001, ** p-value < 0.01, * p-value 0.05		

4.2.2 Model parameter estimates and interpretation

Under this section we highlighted about model selection criteria we used, goodness of the selected model (assumption diagnosis) and interpretation of the model parameters estimates. These tasks were conducted using different techniques as likelihood ratio tests and information criteria to compare fitted models whether it fit the data well or not. We conducted proportional assumption odds diagnosis, and model comparison before interpreting the results of the final model.

Model selection and model goodness diagnosis (assumption checking)

As presented in Table 4.4 below, we select the final model based on the information criteria Akiake's Information criteria (AIC) and also Bayesian Information Criteria (BIC). The Information criteria; AIC and BIC corresponds to null model (the model excluding all predictors) is 10,443.01 and 10,468.93 respectively. AIC and BIC corresponds to an intermediate model (the model including some of predictors at respective level) are 7,521.689 and 7660.664 respectively. AIC and BIC corresponds to full model (with interaction) 7,162.497 and 7,358.536 respectively. finally, AIC and BIC corresponds to the final model (the model that includes all covariates at their respective level and excluding interaction) is 7143.701 7307.541 respectively which are less than the respective former quantities.

According to information criteria it is the model with the smallest AIC and BIC that most fit the data; therefore, in our case the third model was selected to be the final model containing only the main effect provides the best fit of the data since the criteria values corresponds to it is the least of all the other models. Finally, we fit the model that includes all level-one, level-two and level-three at respective levels and we made our interpretation, discussion, conclusion and forward recommendation based on the final model we selected. The model including interaction of predictors shows comparably not as effective fit to the data and shows that interaction effect is not necessary in the table. Indeed this shows that there is no causal effect of predictors on physical development.

Table 4.4: AIC and BIC estimates for all models

Model	Degree of Freedom	AIC	BIC
Null model	4	10443.01	10468.93
Intermediate model(some covariates)	22	7521.689	7660.664
Full model (with interaction)	31	7162.497	7358.536
Full model (without interactions)	16	7143.701	7307.541

After we fit the four models: the null model, an intermediate model, full model with interaction and full model without interaction, we checked for the ordinal logistic regression assumption which is parallel line assumption was conducted and its result shows that it holds for most of covariates and do not hold for some. see AppendixF. We excluded the covariates for which the assumption was not met and fit again the the full model. We also checked for normality of variance of random effects and we found condition was met. The model adequacy test was also done using LRT was $\Lambda = 0.745$ and $p = 0.829 > \alpha = 0.05$ which enable us support the goodness of model fit at 5% level if significance. Therefore the full model which consists of all covariates and without interaction fit the data well at this level of significance.

The results in Table 4.5 present associations between various covariates and BMI of children in Ethiopia. The table also, contains the coefficients of all covariates included in the full model and their level of significance (p-value). It presents the log odds of being in next higher BMI category for different levels of each covariate keep others constant. Taking its exponential we can also interpret odds ratios (the ratio of odds of being in next higher categories for one level of a factor to odds of being in next higher category for reference level of the factors). The overall level of statistical significance was supported as the significance is level $(P = 0.000 < \alpha = 0.05)$.

The log odds of being in higher BMI category for female children is 1.010 (AOR = 2.742, p < 0.001) times more likely than male children keeping other covariates constant at 5% level of significance. This can be interpreted also in terms of odds ratio as the odds of being in the next higher category of BMI is 2.742 times higher for females than males keeping other covaraites constant. The log odds of being in higher BMI category for one to two years, two to three years and three to four years children is -1.112 (AOR = 0.329, p < 0.05), -0.810 (AOR = 0.445 , p < 0.05) and -0.692 (AOR = 0.501 , p = < 0.01) times less likely than under one year infants respectively.

The log odds of being in higher BMI category is 0.577 (AOR = 1.781 = $P < 0.001$) and 0.135 (AOR = 1.144, $p < 0.01$) times more likely for breastfed for one year and less and breastfed for two years compared with those never breastfed respectively keeping other covariates constant. On the contrary, the log odds of being in higher category of weight is -0.671 (AOR = 0.511, $p < 0.05$) times less likely for breastfed for two years and more respectively than never breastfed ones.

This result indicates that breast-feeding status is significantly associated with BMI of children. Children who were breastfed for one year or less has higher odds of being in higher BMI category compared to children who were never breastfed (AOR = 1.781, $p < 0.001$). Children who were breastfed for two years also have higher odds of being higher BMI category compared to children who were never breastfed (AOR = 1.144, $p < 0.01$). However, children who were breastfed for more than two years had lower odds of being in higher BMI category compared to children who were never breastfed (AOR = 0.511, $p < 0.05$).

The study also found that children living in rural areas have lower odds of being in higher BMI category compared to children living in urban areas. The log odds of being in a higher BMI category for rural residents is -0.358 (AOR = 0.699, $p < 0.05$) times less likely than for urban residents keeping other covariates constant. This suggests that children living in rural areas may have a protective effect against overweight and obesity.

Children whose mothers received antenatal care have slightly higher odds of being in next higher BMI category than children whose mothers did not receive antenatal care (AOR = 1.340, $p < 0.05$). Children who were delivered with professional assistance have higher odds of being in the higher BMI range compared to children who were delivered without professional assistance, (AOR = 1.402, $p < 0.05$).

Children who were begin breast-feeding within an hour after delivery have higher odds of being in the higher BMI range compared to children who begin breastfeeding later significant (AOR = 1.357, $p < 0.05$). This result also shows the significance of exclusive breast-feeding since those who begin immediately are more likely to be breastfed exclusively for some time.

Children from wealthier households have higher odds of being in the next higher BMI range compared to children from poorer households keeping other covariates constant. Children from poorer (AOR = 1.278, $p < 0.05$), middle (odds ratio = 1.368, $p < 0.05$), Richer (AOR = 2.031, $p < 0.001$) and Richest (odds ratio = 1.521, $p < 0.01$) and family have their respective odds ratio times higher odds of being in the next higher category of BMI range than children form poorest family respectively setting other covariates constant.

Children with partial or adequate media access have higher odds of being in the next higher BMI range compared to children with no media access at all. Children whose families have partial media access (AOR = 2.014, $p < 0.01$) and adequate media access

(AOR = 1.480, $p < 0.05$) are respective odds ratio times more likely to fall in the next higher BMI range than those whose families have no media access at all setting other covariates constant.

Overall, the results of the multilevel ordinal logistic regression model suggest that a combination of individual, household, and community-level factors are associated with BMI among children in Ethiopia. These factors include child characteristics, socioeconomic status, access to healthcare and information, and nutritional status.

Table 4.5: Summary table of parameter estimates: log OR (β), AOR (θ), significance level (p-value), and 95% CI for $\theta(AOR)$

Covariates	$\beta[AOR]$	SE	P-value	sig. [95% CI for OR]
Child Sex				
Male (ref)				
Female	1.010 [2.742]	0.027	0.000	*** [2.435, 3.050]
Age category in Months				
Under one year				
One to two years	-1.112 [0.329]	0.103	0.031	* [0.267, 0.391]
Two to three years	-0.810 [0.445]	0.071	0.018	* [0.246, 0.643]
Three to Four years	-0.692 [0.501]	0.047	0.007	** [0.225, 0.776]
Four to five years	0.125 [1.133]	0.215	0.061	[0.912, 1.354]
Parents Residence				
Urban (ref)				
Rural	-0.358 [0.699]	0.297	0.025	* [0.571, 0.827]
Breast feeding status				
Never Breastfed (ref)				
Breastfed (for one year)	0.577 [1.781]	0.027	0.000	*** [1.273, 2.289]
Breastfed (two years)	0.135 [1.144]	0.088	0.006	** [1.055, 1.232]
Breastfed ($\geq$ two years)	-0.671 [0.511]	0.200	0.026	*[0.468, 0.554]
Early initiation (EBF)				
Immediately (ref)				
Later after delivery	0.305 [1.357]	1.054	0.014	* [1.234, 1.480]
Vaccination history of child				
Never vaccinated (ref)				
Partially vaccinated	-0.428 [0.652]	0.019	0.029	* [0.571, 0.733]
Completely Vaccinated	-0.608 [0.544]	0.310	0.037	* [0.328 , 0.760]
Antenatal care status				
No Antenatal care (ref)				
Got Antenatal care	0.293 [1.340]	0.290	0.047	* [1.252, 1.428]

Continuation of Table 4.5				
Covariates	$\beta[AOR]$	SE	P-value	sig. [95% CI for OR]
Birth Delivery assistance status				
No professional assistance (ref)				
Got Professional assistance	0.338 [1.402]	1.028	0.011	* [1.039, 1.765]
Post-natal care status				
No Post natal care at all (ref)				
Partially got Post natal care	0.542 [1.719]	0.418	0.000	*** [1.442, 1.996]
Complete Post natal Care	0.695 [2.004]	0.007	0.000	*** [1.735, 2.273]
Parents Wealth index				
Poorest (ref)				
Poorer	0.245 [1.278]	0.10	0.016	* [1.192, 1.363]
Middle	0.313 [1.368]	0.03	0.013	* [1.025, 1.711]
Richer	0.708 [2.031]	0.021	0.000	*** [1.445, 2.616]
Richest	0.419 [1.521]	0.038	0.003	** [1.020, 2.022]
Nutritional Status				
Incomplete Nutrition (ref)				
Partially Complete Nutrition	0.344 [1.410]	1.00	0.329	[0.200, 2.620]
Complete nutrition	2.256 [9.546]	1.219	0.000	*** [3.589, 15.502]
Mass media Access				
No Media access at all (ref)				
Partial media access	0.700 [2.014]	1.182	0.038	* [1.629, 2.399]
Adequate Media Access	0.392 [1.480]	0.760	0.008	** [1.034, 1.927]
Education parents attained				
No education (ref)				
Primary	1.756 [5.789]	0.241	0.000	*** [1.603, 9.974]
Secondary	1.717 [5.570]	0.0375	0.000	*** [2.469, 8.671]
Higher education	1.288 [3.625]	0.017	0.000	*** [1.665, 5.585]
γ_1	0.679	1.000		(0.050, 1.307)
γ_2	3.315	0.075		(2.663, 3.967)
Level 3 (u_i)	0.509			(0.368, 0.703)
Level 2 ($v_{j(i)}$)	0.394			(0.177, 0.877)
σ^2	4.083			
Total Number of Children	***4,825***			
Note: *** p < 0.001, ** p < 0.01, * p < 0.05				

Chapter 5

Discussion

From the descriptive analysis results, over half of the children included in the study are under-weight, which puts them at risk of physical development disorders. Only 34.72% of U5 children in Ethiopia have normal physical growth. The prevalence of UW (52.68%) is substantially higher in Ethiopia compared to the corresponding quantity across the world which is 22%. The prevalence of OW which is 12.60% is also higher in Ethiopia compared to its corresponding quantity which is 5.5% across the world. This indicator (UW) is also higher in Ethiopia compared to its corresponding quantity in Africa which is 41%.

The prevalence of UW is higher for rural residents than in urban residents, while the prevalence of NW is higher for urban residents than for rural residents and the prevalence of OW is similar in both urban and rural areas except slightly higher for urban residents. This indicates that there is a wide range of variety in physical development among children depending on place of residence.

This is likely due to a combination of factors such as: family awareness about healthy dieting habits which can lead to poor dietary choices that contribute to extra weight gain, improper(optimal) breast-feeding practices which protect against underweight and obesity, under-standard availability of healthcare facilities which provide opportunities for children to receive regular checkups and guidance on healthy eating; family education level which is associated with health outcomes, sanitation facility and other factors. Besides the variation can be happen likely due to individual-level factors such as: lack of awareness about appropriate childcare, sub-optimal breast-feeding practices, and low education level, household-level factors like: low economic status and food insecurity and community-level factors like: limited access to media, sanitation, and healthcare facilities, as well as inadequate nutrition. These factors can contribute to childhood development disorders that can lead to various health problems in the future life.

Most of the literature reviewed discuss the health, social and economic benefit of breast-feeding (Victora et al., 2016; Mohammed et al., 2020). Most of research reports stress the practice, recommend and promote its practice. As (Gibson and Campbell., 2017) suggest, breast-feeding is even recommended regardless of its effect on BMI and development. However (Victora et al., 2016) mansion that those researches that support and encourage breast-feeding have been challenged by some opposing arguments. A report American academy of pediatrics asserts that if there are facilities that can substitute breast-feeding and its benefit, as sanitation and medical care, the benefit of breast-feeding will be modest. This contradicting concept is attempts to influence people of developed countries and urban residents and consequently hinders mothers from breast-feeding practice and further reduces the awareness of the world's community about unsubstitutable benefits of breastfeeding.

Based on the findings of our analysis, it was founded that children physical development is affected by a number of predictors among which breast-feeding, our primary concern is the major one. It was also founded that Child sex, age, Residence, Breast-feeding exclusivity, Breast-feeding length in months, Vaccination status, Birth delivery professional assistance, Antenatal care, Postnatal care, Family wealth index, community media access are predictors that significantly contribute to variation in children physical development.

Breast-feeding, a crucial aspect of our study, significantly impacts children's physical development. It serves as a regulatory mechanism, maintaining BMI within a healthy range. At lower breastfeeding levels, increased duration raises the likelihood of a higher BMI category. However, further increasing breastfeeding duration reduces the odds of being in a higher BMI category. This intricate relationship, where coefficients vary in direction at different levels, is also evident for other factors. Our findings underscore the importance of breastfeeding and align with global and national health organizations' recommendations, as well as supportive research evidence. Thus, it was our primary recommendation to promote breastfeeding practices to optimize children's health outcomes.

At the individual level, breastfeeding is linked to a lower likelihood of underweight. This suggests a complex relationship between breastfeeding practices and childhood BMI. While shorter breastfeeding duration (one year or less) may increase the odds of being in higher BMI category, longer breastfeeding duration (over two years) may decrease these odds. Further research is needed to elucidate the mechanisms behind these. These findings align with prior studies demonstrating the association of breast-feeding with various health benefits for children, including reduced obesity and chronic disease risk.

Consistent with previous researches (Gibson and Campbell., 2017; Victora et al., 2016, 2021; Jones et al., 2017; Quinn et al., 2001; Chen et al., 2022), have shown that breastfeeding is significantly associated with a number of health benefits for children as well as for mothers, including a reduced risk of obesity and other chronic diseases and ensures healthy physical development.

Among household-level factors, children from wealthier households have higher odds of being in the normal BMI range. This is likely due to the fact that wealthier households have better access to food and healthcare, and are more likely to live in environments that support healthy eating and physical activity. Access to media, cleaning facility, health facility and are also found to be statistically significant factors that influence the physical development of U5 children.

As children get older, their odds of being in the normal BMI range decrease. This is likely due to the fact that older children are more likely to consume unhealthy foods and bebidas, and are less likely to be physically active. Female children have slightly higher odds of being in the normal BMI range compared to male children. There is no clear pattern in the association between postnatal care status and BMI. This suggests that postnatal care may not play a significant role in determining BMI.

Implications

Future research is needed to:

- Establish causal relationships: Conduct longitudinal studies to establish causal relationships between the predictor variables and BMI.
- Explore other factors: Explore other factors that may be associated with BMI, such as maternal nutrition and physical activity.
- Develop and evaluate interventions: Develop and evaluate interventions to improve the nutritional status of children in Ethiopia.

In summary, breast-feeding for one year and less (AOR = 1.785, $p = < 0.001$), breast-feeding for two years (AOR = 1.144, $P < 0.01$) and breast-feeding for two years and above (AOR = 0.511, $p < 0.05$) are has been found statistically significant factor of physical development of U5 children in Ethiopia. Similarly, Vaccination status: partial vaccination (AOR = 0.652, $P < 0.05$) and complete vaccination (OR = 0.544, $P < 0.05$) is significant factor. likewise community media access, mothers education level, health facility, family economic status, ANC, PNC, professional delivery assistance, nutritional status, sex, age, residence are statistically significant determinants of U5 children physical development at 5% level of significance.

Chapter 6

Conclusion and recommendation

6.1 Conclusion

The analysis of factors influencing child physical development in Ethiopia provides valuable insights into the potential role of breast-feeding practices, demographic factors, and child health outcomes. The observed associations suggest that promoting breast-feeding, particularly exclusive-breastfeeding and early initiation, may contribute to healthier weight outcomes in children. However, the complex interplay of factors, including socio-economic status, access to healthcare, and cultural norms, warrant further investigation to fully understand the causal relationships. Overall, the findings of this study provide important insights into covariates associated with BMI among children in Ethiopia. These findings can be used to inform public health policy makers, social practitioners and project (program) developers, to develop and evaluate interventions to improve the nutritional particularly breast-feeding status of children in Ethiopia.

6.2 Recommendation

Breastfeeding is a major predictor of children's physical development. Its impact on BMI is complex and varies depending on the level of breastfeeding. Other factors such as child sex, age, residence, and access to healthcare also contribute significantly to children physical development. It is important to address these factors in order to reduce the prevalence of over-weight and obesity and to improve the health and well-being of Ethiopian children. This can be done through education campaigns, community-based interventions, and policy changes that promote healthy eating and physical activity.

Further research is needed to explore the complex relationship between breastfeeding and physical development, as well as the impact of other predictors. Interventions should be developed to address factors that hinder optimal breastfeeding practices. Monitoring and evaluation of breastfeeding promotion programs is crucial to ensure their effectiveness in improving children's physical development.

To promote optimal physical development, it is recommended to:

- Encourage exclusive breast-feeding for the first six months of life and continued breastfeeding for up to two years or beyond.
- Educate parents and caregivers about the appropriate dieting of children to ensure the healthy physical development.
- Implement policies, programs and projects that support appropriate nutritional

system of particularly breast-feeding.

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Appendices

Appendix A

The probability of BMI being in category C or less assuming level-two random effect is insignificant

Let $Y_{j(i)k}$ denote the response variable for the k^{th} observation in the j^{th} level-two unit nested within the i^{th} level-three unit and The predictor variables are denoted as $X_{j(i)k}$, The cumulative probabilities that response occur in ordered categories $1 < 2 < 3$ can be given as follows.

$$\begin{aligned} P(Y_{j(i)k} \leq 1) &= \Phi(\alpha_1 + \alpha_{i1} + \mathbf{Z}_i^T \mathbf{b}_i + \beta_1 X_{j(i)k}) \\ P(Y_{ijk} \leq 2) &= \Phi(\alpha_2 + \alpha_{i2} + \mathbf{Z}_i^T \mathbf{b}_i + \beta_1 X_{j(i)k}) \\ P(Y_{ijk} = 3) &= 1 - \Phi(\alpha_3 + \alpha_{i3} + \mathbf{Z}_i^T \mathbf{b}_i + \beta_1 X_{j(i)k}) \end{aligned} \tag{A.0.1}$$

Where: $\Phi(.)$ Is the cumulative distribution function of a logistic (or other suitable) distribution, $\alpha_1, \alpha_2, \alpha_3$ Are the intercept parameters corresponding to the cut-off points between each pair of adjacent categories at the level of individual observations, $\alpha_{i1}, \alpha_{i2}, \alpha_{i3}$ Are the level-three random intercept parameters, $\mathbf{Z}_{ij}$ Is the design matrix for the level-three predictors (random effects), $\mathbf{b}_i$ Is the vector of level-three random effects and β_1 Is the regression coefficient for the level-one predictor variable X_{ijk}.

$$\begin{aligned} logit(p_{j(i)k0}) &= \alpha_{0i} + \alpha_{0j(i)} + \beta_1 X_{j(i)k} + b_{j(i)k} \\ logit(p_{j(i)k1}) &= \alpha_{1i} + \alpha_{1j(i)} + \beta_1 X_{j(i)k} + b_{j(i)k} \\ logit(p_{j(i)k2}) &= \alpha_{2i} + \alpha_{2j(i)} + \beta_1 X_{j(i)k} + b_{j(i)k} \\ &\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ logit(p_{j(i)kc}) &= \alpha_{ci} + \alpha_{cj(i)} + \beta_1 X_{j(i)k} + b_{j(i)k} \end{aligned} \tag{A.0.2}$$

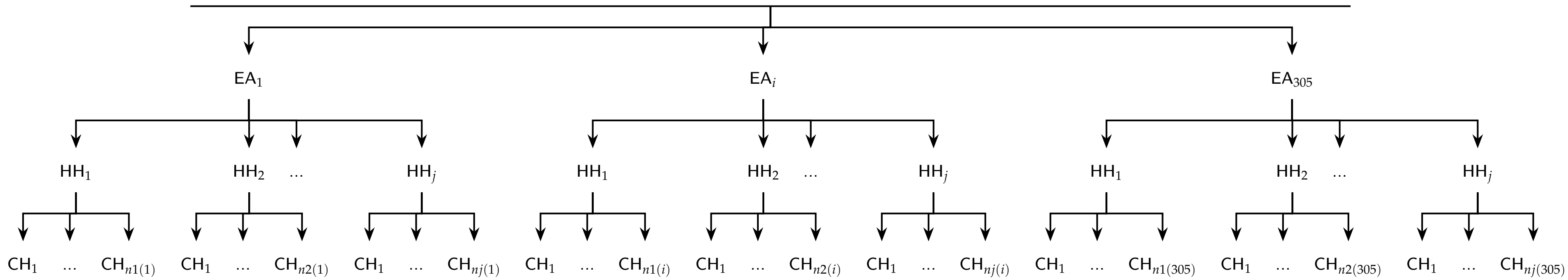
Where: $p_{j(i)k0}, p_{j(i)k1}, p_{j(i)k2}$ represent the probabilities of observing categories 0, 1, and 2, respectively, for the i^{th} observation in the j^{th} group within the k^{th} cluster, X_{ijk} represents the covariates for the i^{th} observation in the j^{th} group within the k^{th} cluster, β_1 represents the fixed effect coefficient, $\alpha_{0k}, \alpha_{1k}, \alpha_{2k}$ are the intercepts for each category at the cluster level, $\alpha_{0j(i)}, \alpha_{1j(i)}, \alpha_{2j(i)}$ are the intercepts for each category at the group level within the cluster, $b_{j(i)k}$ represents the random effect for the i^{th} observation in the j^{th} group within the k^{th} cluster.

Appendix B

Data generating mechanism

Hierarchy of data generating mechanism

305 EA's selected next HH of different size selected from each EA's and finally all eligible children of less than 59 months old were selected and observed.



EA = 1, 2, i, .., 305

HH = 1, 2, j, ..., maximum number of HH in each EA

n = 1, 2, ..., total number of children participated in the study. which is 4825.

Appendix C

Graphical presentation of under-weight, normal-weight and overweight in each Enumeration Area

The maximum number of under-weight is in 193^{th} EA, the maximum number of Normal-weight is in 15^{th} EA and maximum number of over-weight is in 252^{th} EA. This results shows that the maximum number of under-weight occurs in SNNP, maximum number of normal-weight is observed in Tigrai region and maximum number of over-weight is observed in Harari and somale region.

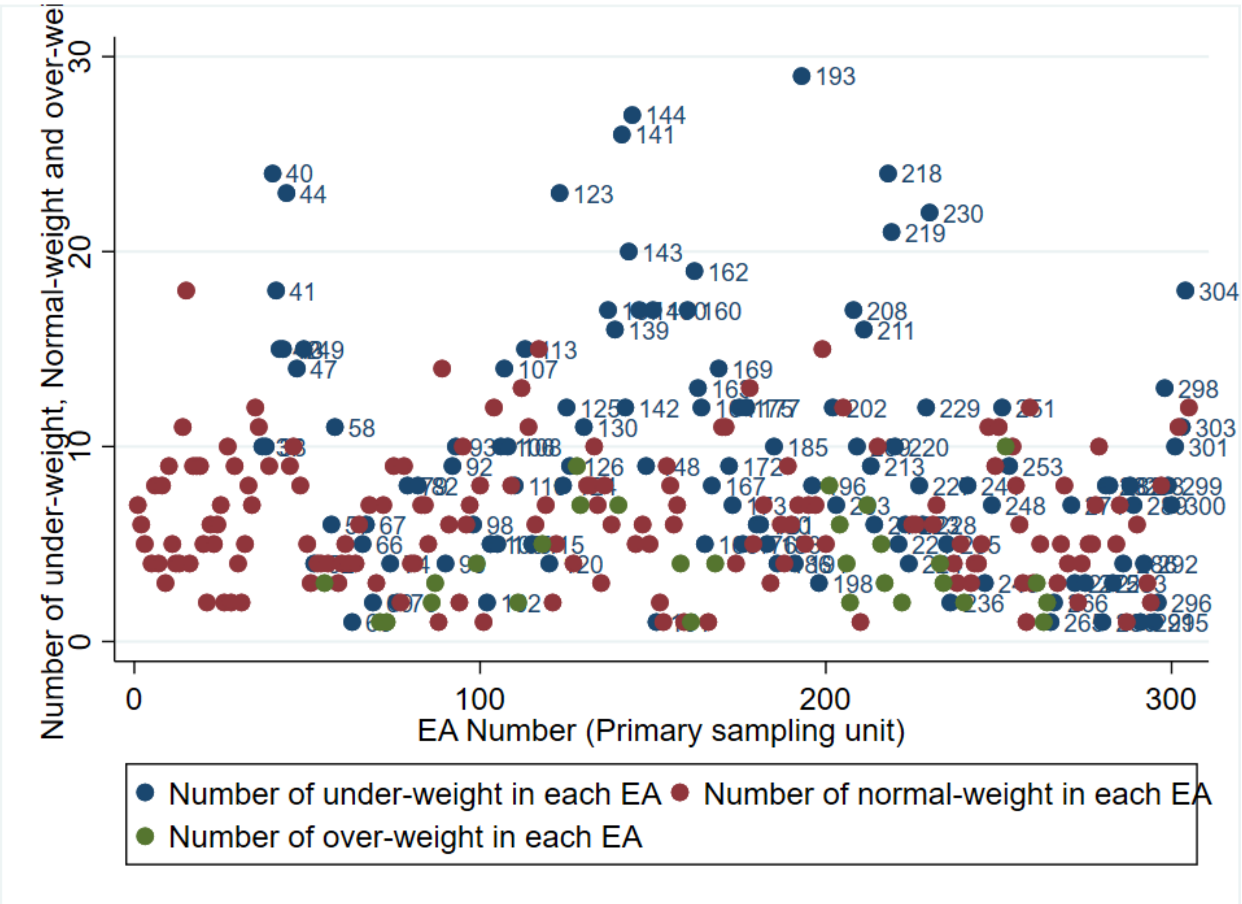


Figure C.1: Histogram of Transformed BMI of children

Appendix D

Distribution of Body mass index of under-five children.

This appendix presents the normal distribution of continuous BMI of U5 children. It shows that the BMI of U5 is normally distributed having mean 15.318, median 15.388 and standard deviation 2.061.

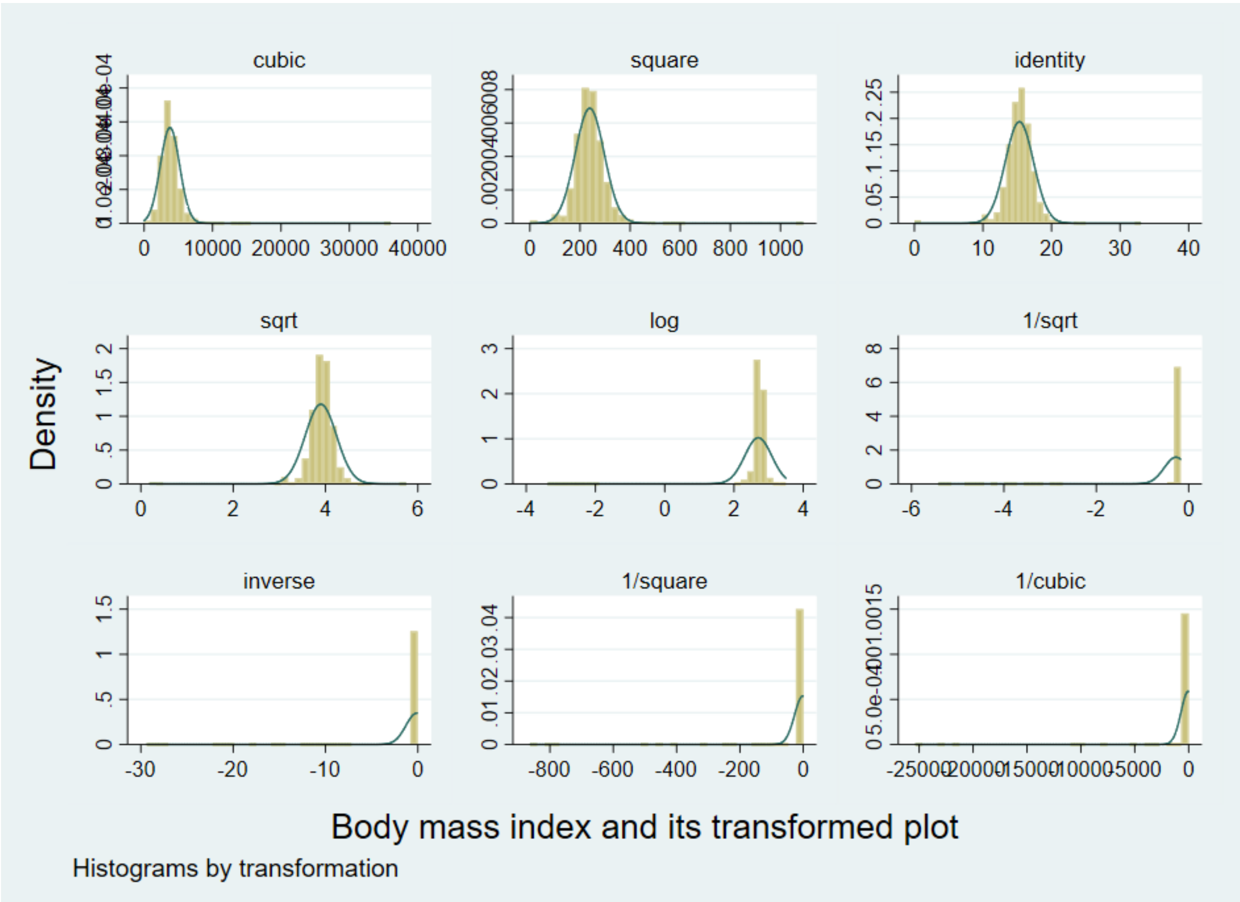


Figure D.1: Scatter plot of UW, NW & OW by EA

Appendix E

Categorized and Transformed BMI of chiuldren

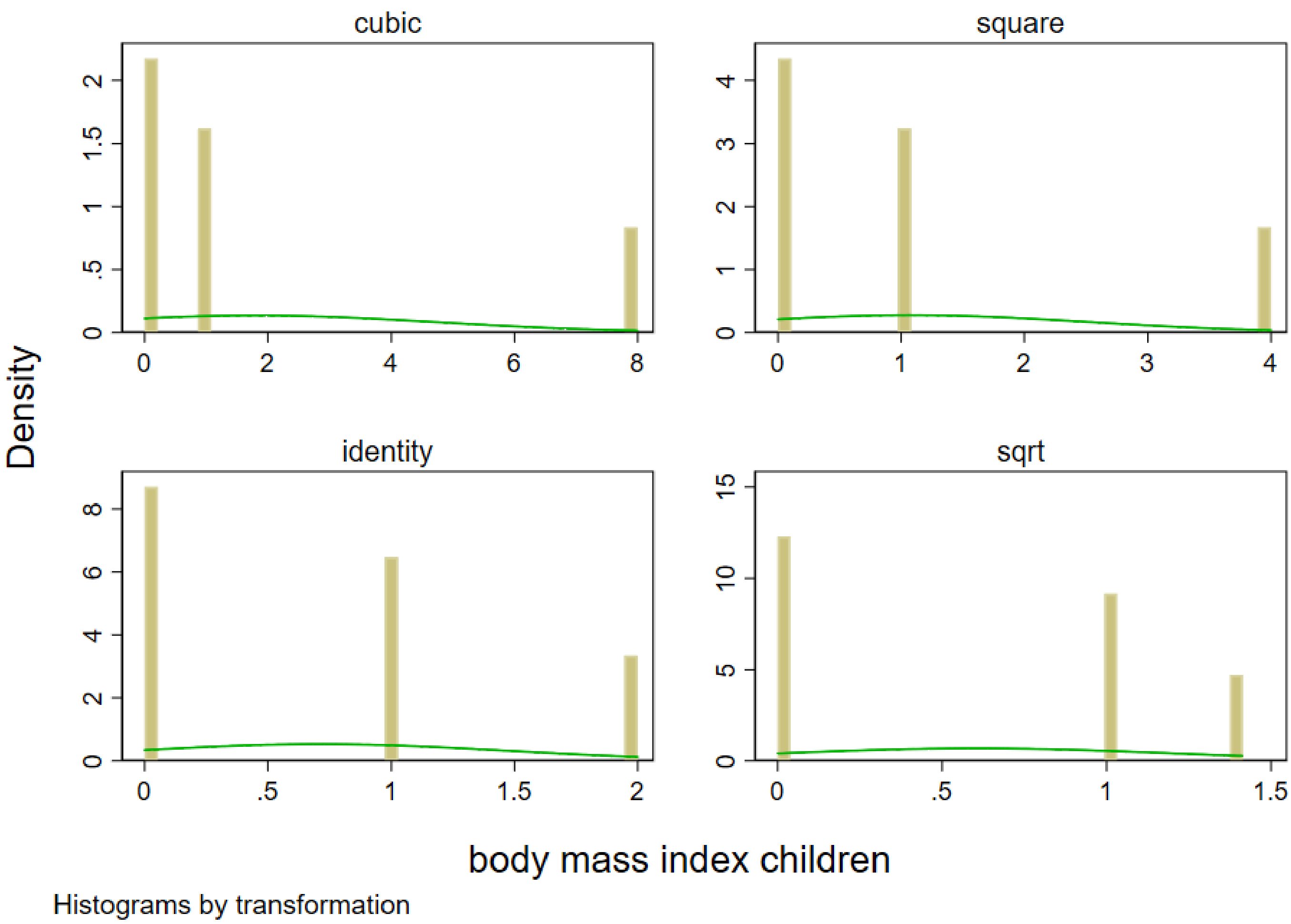


Figure E.1: Histogram of categorised BMI

Appendix F

Proportional odds assumption checking

This table shows that the effect of breastfeeding is the same for all categories of Body mass Index. As an example, the log odds of being at underweight is 61% less for children breastfed for one year than those never breastfed. this effect is also the same for being normal weight. This result shows that Proportional odds model hold for breast-feeding and birth delivery professional assistance.

BMIU5	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Under-weight						
BFS						
Breastfed for less than one year	.3041176	.1677689	1.81	0.070	-.0247034	.6329386
Breast fed for two years	.2223129	.1858412	1.20	0.232	-.1419292	.586555
breast fed for above two years	-.1018329	.2029986	-0.50	0.616	-.4997028	.296037
DAS						
Professional Assistance	.0660807	.0848496	0.78	0.436	-.1002214	.2323829
MA						
have TV or Radio	.0917207	.088266	1.04	0.299	-.0812775	.2647188
have no media devices	.1030968	.1504584	0.69	0.493	-.1917962	.3979897
CHVS						
partially vaccinated	.2156495	.0980854	2.20	0.028	.0234057	.4078932
Completely vaccinated	-.8284597	.1058022	-7.83	0.000	-1.035828	-.6210913
MANC						
Get antenatal care	-.0481425	.0959738	-0.50	0.616	-.2362477	.1399626
PNCS						
Partial care	-.0935572	.1292311	-0.72	0.469	-.3468456	.1597312
Complete Care	.1166205	.1877805	0.62	0.535	-.2514224	.4846635

(a)

NUTS						
Partially complete nutrition	-.1019778	.0923744	-1.10	0.270	-.2830283	.0790726
Complete nutrition	-1.542301	1.154129	-1.34	0.181	-3.804353	.7197503
v190						
poorer	.3925911	.0974266	4.03	0.000	.2016384	.5835438
middle	.4991688	.1075069	4.64	0.000	.2884592	.7098783
richer	.8393822	.1177051	7.13	0.000	.6086843	1.07008
richest	.5160294	.1342703	3.84	0.000	.2528646	.7791943
v106						
primary	.0319073	.0760736	0.42	0.675	-.1171943	.1810089
secondary	.19228	.126693	1.52	0.129	-.0560338	.4405937
higher	.0160621	.1590209	0.10	0.920	-.2956132	.3277374
b4						
female	.9114761	.0651634	13.99	0.000	.7837582	1.039194
_cons	-.817738	.2331517	-3.51	0.000	-1.274707	-.3607691

(b)

Normal_wieight						
BFS						
Breastfed for less than one year	.3041176	.1677689	1.81	0.070	-.0247034	.6329386
Breast fed for two years	.2223129	.1858412	1.20	0.232	-.1419292	.586555
breast fed for above two years	-.1018329	.2029986	-0.50	0.616	-.4997028	.296037
DAS						
Professional Assistance	.0660807	.0848496	0.78	0.436	-.1002214	.2323829
MA						
have TV or Radio	.0917207	.088266	1.04	0.299	-.0812775	.2647188
have no media devices	.1030968	.1504584	0.69	0.493	-.1917962	.3979897
CHVS						
partially vaccinated	.2156495	.0980854	2.20	0.028	.0234057	.4078932
Completely vaccinated	-.8284597	.1058022	-7.83	0.000	-1.035828	-.6210913
MANC						
Get antenatal care	-.0481425	.0959738	-0.50	0.616	-.2362477	.1399626
PNCS						
Partial care	-.0935572	.1292311	-0.72	0.469	-.3468456	.1597312
Complete Care	.1166205	.1877805	0.62	0.535	-.2514224	.4846635

(c)

NUTS						
Partially complete nutrition	-.1019778	.0923744	-1.10	0.270	-.2830283	.0790726
Complete nutrition	-1.542301	1.154129	-1.34	0.181	-3.804353	.7197503
v190						
poorer	.3925911	.0974266	4.03	0.000	.2016384	.5835438
middle	.4991688	.1075069	4.64	0.000	.2884592	.7098783
richer	.8393822	.1177051	7.13	0.000	.6086843	1.07008
richest	.5160294	.1342703	3.84	0.000	.2528646	.7791943
v106						
primary	.0319073	.0760736	0.42	0.675	-.1171943	.1810089
secondary	.19228	.126693	1.52	0.129	-.0560338	.4405937
higher	.0160621	.1590209	0.10	0.920	-.2956132	.3277374
b4						
female	.9114761	.0651634	13.99	0.000	.7837582	1.039194
_cons	-3.278351	.2399906	-13.66	0.000	-3.748724	-2.807978

(d)

Figure F.1: Proportional Odds assumption checking using (parallel line assumption)

Appendix G

WHO, CDC and IOTF developed children physical development measurement tools and BMI cut points

Table G.1: The different measurement tools developed by World Health Organization, Center for Disease control and Prevention,Internationale Obesity Task Force

		WHO	CDC	IOTF(male(female))
Age category	Tools	unit of measurement	unit of measurement	unit of Unit of measurement
(0<20 years)	LA/HA (Stunting)	$p<3.00$	$p<5.00$	-
	Normal height	$p \geq 3.00$	$p \geq 5.00$	-
0<5 years	BMI-for-age (Severe thinness)	$p<0.10$	-	-
	Thinness	$0.10 \leq p < 3$	$p<5.00$	$p<15.50$ ($p<6.50$)
	Normal weight	$3 \leq p \leq 85$	$5 \leq p < 85$	$15.50 \leq 90.50(16.50 \leq p < 89.30)$
	Risk of overweight	$85.00 < p \leq 97.00$	-	- -
	Overweight	$97.00 < p \leq 99.90$	$85 \leq p < 95$	$90.50 \leq p < 98.90(89.30 \leq p < 98.60)$
	Obesity	$p>99.90$	p95.00	$98.90 \leq p < 99.83(98.60 \leq p < 99.76)$
	Morbid obesity	-	- p99.83(p99.76)	
5<20 years	BMI-for-age (severe-thinness)	$p<0.10$	-	-
	Thinness	$0.10 \leq p < 3.00$	$p<5.00$	$p<15.50$ ($p<16.50$)
	Normal weight	$3.00 \leq p \leq 85.00$	$5.00 \leq p < 85.00$	$15.50 \leq p < 90.50(16.50 \leq p < 89.30)$
	Overweight	$85.00 < p \leq 97.00$	$85.00 \leq p < 95.00$	$90.50 \leq p < 98.90(89.30 \leq p < 98.60)$
	Obesity	$97.00 < p \leq 99.90$	$p \geq 95.00$	$98.90 \leq p < 99.83(98.60 \leq p < 99.76)$
	Morbid obesity	$p>99.90$	-	$p \geq 99.83(p \geq 99.76)$

* Note: We have converted these percentiles to real number and used in the analysis directly (Racette et al., 2017)

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 material used for the thesis have been duly acknowledged.

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Signature: ________________

Place: College of Natural and Computational Sciences, Addis Ababa University

Date: ______________

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

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Prof. Eshetu Wencheko