QUANTILE REGRESSION MODELLING OF FACTORS INFLUENCING NUTRITIONAL STATUS OF UNDER-FIVE CHILDREN IN NIGERIA

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ABSTRACT

BACKGROUND

Body Mass Index (BMI) is a measure of under-five children nutritional status and a proxy for a nation's economic future productivity. BMI may not always satisfy the normality assumptions when studied with parametric models, restraining comprehensive assessment of the explanatory variables. Limiting health challenges has been associated with extreme values of the BMI. The study investigated the factors associated with the nutritional status of under-five children measured by BMI and explored its full distributional effect using quantile regression model.

METHODS

Nationally representative records of under-five children was obtained from the Multiple Indicator Cluster Survey round 5 (MICS5 – 2016/2017). The outcome variable was BMI defined as weight in kilograms per height in metres squared (kg/m^2). The explanatory variables were age (months), sex, location of residence, mothers' level of education, geopolitical region, parent's wealth status and household size. Descriptive statistics such as frequency tables and proportions were used to summarize categorical variables, median and IQR for continuous variables, skewness and kutorsis to measure the spread and peakedness of BMI, the test of normality was performed BMI and the pseudo R^2 to measure the model goodness of fit. The Quantile regression model was fitted using selected conditional quantiles, with their respective 200 resample bootstrapped standard error at 95% confidence level.

RESULTS

Of the 27,766 total records, 14,048 (50.6%) were male children. The median BMI of male children was slightly higher (15.44 kg/m^2, IQR=1.92) than the median BMI of female children (15.11 kg/m^2, IQR=1.91). The skewness and kurtosis of the total participants BMI were 1.20 and 15.13 respectively and the test of normality on BMI was statistically significant. Male children were more likely to have increased BMI compared to the female children with coefficients of 0.23, 0.33 and 0.27 at the 5th, 85th and 95th quantile respectively. Location of residence was associated with BMI at the 85th quantile for female participants. By geopolitical region, North Central was associated with BMI at the 25th, 50th, and 75th quantile for all children. Age, sex, mothers' level of education, geopolitical region, and parent's wealth status of both male and female children were associated with BMI. The model summary revealed that the pseudo R^2 decreased with increasing quantiles.

CONCLUSION

Quantile regression provides a comprehensive insight to how the covariates vary across the BMI distribution. The inherent characteristics of the children's BMI was characterized by a significant test of normality, revealing the great importance of the quantile regression model. The findings of this study further showed a relatively low BMI of the children indicating that the nutritional status of children is still a problem of public health importance.

KEYWORDS: Nutritional status, Body Mass Index, Quantile Regression Model, Under-five Children.

WORD COUNT: 426 words

CERTIFICATION

I certify that this work titled "Quantile Regression Modelling of Factors Influencing Nutritional Status of Under-Five Children in Nigeria" was carried out by OLOWOYEYE, Oluwatosin Rotimi, in the Department of Epidemiology and Medical Statistics, Faculty of Public Health, University of Ibadan under my supervision.

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DEDICATION

Efforts without support and grace amount to nothing, in this wise, I supremely dedicate the success of this project the crown of my master's degree programme to Almighty God "Yahweh," the Alpha and Omega of my existence, well-being and exploits.

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CHAPTER ONE

1.0 INTRODUCTION

1.1 BACKGROUND OF THE STUDY

The word “quantile” is used to describe concepts like quartile, quintile, decile and percentiles meaning partitioning into four, five, ten and hundred equally-sized parts respectively. It originated from the Latin word “quantus” meaning how much or how great a value is. It is defined as each of any set of values of a random variable which divide a frequency distribution into equal parts, with each part having the same proportion of the entire values collection. (Aronson, 2001)

Considering the popularly attributed quantile to distribution of a dataset; the quartile partitioning is used in determining the shape exhibited by such dataset. The first quartile (Q1) provides a measure of about 25% of the distribution below this point, the second quartile (Q2) partitions the dataset distribution into two halves where about 50% of the observations lie above and below this point, whereas the third quartile (Q3) provides a measure of about 75% of the observations below this point.

The quartile partitioning of a set of observations gives an absolute definition to the type of skewness if any or state of normality to a given set of data. For instance, if the difference between the third quartile and the second quartile equals the difference between the second quartile and the first quartile, the distribution of the given set of data is normally distributed. Whereas, if the difference between the third and second quartile exceeds the difference between second and first quartile, the distribution of the given set of data is positively skewed, otherwise, it is negatively skewed.

The linear regression model has been used to model continuous outcome measures with several independent variables, utilizing the conditional mean of the outcome variable i.e., describing the mean of the outcome variable for a fixed value of the independent variable. The linear regression is characterized by limitations such as: non-extension to non-central location of a distribution, failure of applicability of its assumption like homoscedasticity and finally lack of investigative power to explore full distribution of the response variable (Hao and Naiman, 2007).

But when the distribution of the outcome variable is not normally distributed the median regression model provides a better estimate of the central measure when the outcome variable is skewed, replacing the least square methods of the linear regression model with least absolute distance estimation, this least absolute distance estimation is eased by the advent of computing technology and algorithmic synergy (Hao and Naiman, 2007).The median regression model absorbs the skewed nature of the outcome variable but still do not permit full exploration i.e., of other non-central quantile (e.g. 0.10, 0.25, 0.75, 0.90, etc) of the outcome distribution.

In contrast to the use of the conditional mean of the outcome variable to measure the changes associated with the predictors by the linear regression model, quantile regression model uses the conditional quantile of the outcome variable as functions of the covariates, giving it more flexibility to explore full distribution of the outcome variable (Carvini, 2010)

The quantile regression model gained more acceptability in its application about fifteen years after introduction in 1978, has a special case of the median regression model; its only central quantile measure which is the 0.5th conditional quantile regression model. The quantile regression shares some attributes such as modelling continuous response variables and linearity nature of the unknown model parameters with the linear regression, adapting differences in terms of quantities modelled and assumptions about the error term (Yusuf *et al,* 2017). Quantile regression model is heteroscedastic in nature, robust to outliers and allows shape changes due to its ability to permit dependent variable to vary with the independent variable.

Quantile regression basically characterize the relationship between the dependent variable's distribution and the covariates, and shows how changes in the covariates have an effect on the shape of the response variable's distribution (Koenker, 2005). It gives a comprehensive view of the relationship between the response and the predictor variables by utilizing the conditional quantile of the response distribution.

Generally, the pth quantile gives the value of the outcome below which its proportion of the whole distribution is p. Considering the 3.5% of the whole distribution, this resides below the 0.035th quantile.

In relation to the cumulative distribution function (cdf) of a random variable x, which is the proportion of the population X <x, the pth quantile of such random variable is the inverse value of the random variable's cdf at p. This implies that if the cdf is denoted by F(x) and the quantile by p, we have F(x) = p. Taking the standard normal distribution into account, F(x) (1.0) = 0.8, therefore, Q(0.8) = 1.0, this means that the proportion of the standard normal population below 1.0 is 0.8 or 80%.

1.2 PROBLEM STATEMENT

Poor nutrition leads to reduced immunity, higher susceptibility to disease, impaired development and reduced productivity. Proper nutrition assures good nutritional status of children for their growth and development. In view of the projected challenges attributed to obesity, WHO in 2014 established The Commission on Ending Childhood Obesity, this commission has the mandate of reviewing, addressing gaps in existing childhood nutritional programme mandates and strategies (WHO, 2016).

Overweight and obesity is attributed to over-nutrition, children who grows with obesity till adulthood have a significant higher cost of both inpatient and outpatient compared to non-obese individual placing higher economic burden on the individual and healthcare facilities (Umaru *et al*., 2019).

Under-five overweight predicament include, low cardio-respiratory fitness, decline in physical activity and lack of adequate sleep resulting in an increase in diastolic and systolic blood pressure. Imbalance energy intake and release tends to obesity most especially in children aged three years who has been exposed to solid food before fourth month of birth.

Under-five obesity is associated with acute complications such as orthopaedic disorders i.e., bowing of the tibia and femurs, cardiovascular and endocrine disorder, liver and gall bladder dysfunction, psychologic complications from peer bullying causing depression. In adulthood complications such as type 2 diabetes, cardiovascular disease and psychosocial dysfunction are attributed to obesity.

There is a global increase in under-five obesity, as there are more children affected by this in low-and-middle income countries. Global prevalence of childhood overweight and obesity increased from 4.2% in 1990 to 6.7% in 2010, more overweight and obese children are in developing countries than developed countries in 2010, 35 million of the total 43 million children. The prevalence is higher in Africa by 4.9% in 2010 than Asia (De Onis, Blo¨ssner, and Borghi, 2010).

The National Health and Nutrition Examination Survey (NHANES) reports that the prevalence of obesity is on the increase in all pediatric ages (NHANES, 2019). Childhood obesity defined as having more weight than the body can carry, is associated with factors such as genetic, environmental, metabolism, lifestyle and eating habit. Metabolic abnormalities such as raised cholesterol, triglycerides and glucose, type 2 diabetes, and high blood pressure are some of the immediate consequences attributed to childhood obesity, which is also a strong risk factor for adult obesity and inherent for their children (WHO, 2016).

Below the healthy weight is underweight defined as low weight-for-age i.e., the child is too thin for his/her age, globally its prevalence was projected to decline from 26.5% in 1990 to 17.6% in 2015, but Western Africa is expected to experience substantial increase in the number of underweight children (De Onis. *et al,* 2004).

Undernutrition accounts for about half of mortality in under-five children globally, this puts children at higher risk of death from common infection, severity of infection and delayed recovery. World Health Organization in 2016 estimated a prevalence of about 31.5% underweight children in Nigeria (WHO, 2016).

Underweight in children residing in Western Africa is currently estimated to be 15%. In Nigeria, the national prevalence of underweight among under-five children is 19.9% corresponding to rates in other Western and Central Africa region. The North West region has the highest prevalence of 29.7% and the lowest in South East region with prevalence of 12.6% with the WHO underweight critical threshold at 30% (NNHS, 2018).

For more than two centuries, in the field of statistical modeling, the development of regression statistical model has helped to quantify the relationship between the response and explanatory variables. Majorly, the linear regression model has been commonly used to estimate the effects at the mean. This is based on the assumption that estimates of effect are constant across the study population, however, this might not be applicable in some areas resulting from the exhibition of heterogeneity (Huang *et al,* 2017)

In addition to the possibility of deviation from homogeneity, increasing complexity has been associated with data in research analytics requiring a versatile, robust and scalable methods for building predictive statistical models which the linear regression model cannot model comprehensively, quantile regression model assumes no parametric assumptions for the conditional distribution of the outcome variable, yielding an enormous insight in its application (Rodriguez, Yao and SAS, 2017)

Attention has shifted from averages to group differences across the entire population as observed by clinicians and policy makers (Collins and Varmus, 2015; Zhou, 2011). This complete insight of the behaviour of the covariates across the conditional distribution quantile of the response variable affords the quantile regression its relevance of better conclusion when the normality assumption of the linear regression model fails in statistical modeling.

Hence, quantile regression offers a considerable model robustness, measures the impact of covariates at different quantile of the outcome distribution giving a complete description of the relationship between the outcome and explanatory variables, it also provides a flexible application of the link function and distributional assumptions as exhibited by the linear regression model (Yirga, Ayele and Melesse, 2018)

1.3 JUSTIFICATION OF THE STUDY

The nutritional status of children especially the under-five year old serves as a good indicator of their parents' socio-economic background and the economic situation of a country. High rates of overweight/obesity is synonymous with developed countries and developing countries with high rates of underweight and it associated malady (WHO, 2018).

Under-five children's health metrics assessed through their nutritional status provides a valuable measure of the health, well-being and social status of any society, this inevitably demands constant and continuous monitoring of characteristics related to their malnutrition. Body mass index levels below and above the healthy weight are associated with great limitation on childhood development, children's educational attainment and their quality of life (WHO, 2016).

The nutritional status of under-five children can be assessed through physical observation, biochemical methods and anthropometric methods. Global acceptability, ease of application and relatively low cost has made the anthropometric method preferable to other methods (Amadi *et al,* 2018), most importantly in low-middle-income countries.

Biometric measurement such as body mass index is not usually normally distributed, non-normality makes the widely utilized statistical tools like the linear regression in assessing factors associated with nutritional status determinants and logistic regression in assessing the odds of these factors associated with nutritional status determinant inappropriate due to the failure of the normality assumption (Beyerlein *et al,* 2008). Quantile regression has a robust characteristic of being insensitive to outliers and model assumptions violation to accommodate the distributional nature of body mass index when not normally distributed.

Many studies have been done on children's nutritional status assessed by their BMI (Acquah *et al,* 2019; Beyerlein *et al,* 2011), but mostly considered category below or above the healthy status, but this study considers the entire distribution of the nutritional status giving a comprehensive description as to the progression from healthy status to underweight and healthy status to overweight/obesity in children nationally across their body mass index.

The flexible nature of the quantile regression model with the utilization of the continuous nature of the outcome variable provides an estimate of the nutritional status determinants effect to be determined throughout the conditional distribution of the outcome variable "body mass index" from an extreme point of being underweight to the extreme point of being obese .

Few studies have been able to associate the extreme points of childhood body mass index distribution with its associated factors. Quantile regression explores the full conditional quantile distribution of the response variable, providing an efficient estimate of the effect of the predictors as compared to the traditional regression model utilizing the conditional mean of the response variable (Beyerlein *et al,* 2008)

1.4 STUDY OBJECTIVES

1.4.1 GENERAL OBJECTIVE

- The main objective of this study is to assess the factors associated with under-five children nutritional status in Nigeria across the different quantiles of their BMI.

1.4.2 SPECIFIC OBJECTIVE

1. To ascertain the state of normality of the children BMI
2. To determine factors affecting the nutritional status of under-five children in Nigeria
3. To assess the magnitude and direction of nutritional status determinants across different quantile of the outcome distribution.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 OVERVIEW OF MALNUTRITION

Childhood malnutrition accounts for one of the most vital causes of morbidity and mortality especially in developing countries (Gebre *et al,* 2019). Malnutrition is a measure of relative deficiency or extreme abundance of one or more essential body nutrients (Varma and Prasad, 2017). This may also yield a long-term challenge that is irreversible, these includes delayed cognitive and poor physical development (dos Santos *et al,* 2018). It further reduces sensory-motor abilities, reproductive capacity and make children more susceptible to hereditary diseases inhibiting productivity in working productivity at adulthood (WHO, 2020)

Studies by (Darsene *et al,* 2017; Mengistu, Alemu and Destaw, 2013) have shown that deviations from healthy nutritional status in children may lead to an increase level of chronic illnesses at adult stage in life, with its intergenerational effects yielding births of low-weight babies for female adults.

Malnutrition is defined as the lack of proper nutrition this can be caused by not having enough to eat, not eating enough portions of the right things or being unable to use the food one consumes. It has three key major strands: under-nutrition, hidden hunger and overweight with its often severe state of obesity (UNICEF, 2019).

Recent study by UNICEF reveals that globally, almost 200 million under-five children were affected by stunting, wasting or both and at least 340 million from the hidden hunger of vitamins and mineral deficiencies. Likewise, 40 million under-five children were overweight and the statistics from overweight and obesity kept rising even in developing countries. These reflect the unhidden effect of the triple burden of malnutrition as that which threatens the growth and development, survival of children and of nations (UNICEF, 2019)

It was reported by WHO in 2020 that the elimination of malnutrition will yield an estimated 32% removal of the global diseases burden (WHO, 2020).

2.2 CAUSES OF MALNUTRITION

According to UNICEF (1998), there are three causal factors of malnutrition; immediate, underlying ("biological and behavioural" and "social and economic") and basic causes. Food intake and infections represent the immediate causes of malnutrition, underlying causes are causal factors that pave way for immediate causes, these include; food in-security, lack of access to health services and unhealthy environment, basic causes include; political and economic factors and socio-cultural environment.

As a result, malnutrition is related to poverty which is affected by factors such as economic status, maternal education, climate changes, food production, the effectiveness of nutrition programmes and reliability of health services (WHO, 2009).

2.3 NUTRITIONAL STATUS

Nutritional status according to National Cancer Institute (NCI) is the state of an individual's health in relations to the nutrients in his or her diet. It is also the state of a person's body in terms of the consumption and utilization of nutrients. Nutritional assessment is the procedural activity of collecting and interpreting dietary information in order to make decisions about the nature and cause of nutrition-related health issues that affects an individual or a specified population (BDA, 2012). Gibson (2005) defined nutritional assessment as the translation of results from dietary, biochemical, anthropometric and clinical data, used in defining the nutritional status of an individual or specified population as determined by their utilization and intake of food nutrients.

The body of an individual needs an optimal quantity of dietary nutrients to sustain healthy life not in a state that is below or above optimal status to guide against malnutrition and its associated health adverse consequences. Assessment of the nutritional status of an individual helps to promote health, prevent and treat diseases. The goal of nutritional assessment includes: identification of people at risk of malnutrition for early support and referral (before malnutrition sets in), track child's growth, identification of medical complications that affects the body's ability to digest food and utilization of nutrients, inform nutrition education and counselling and aids in establishing appropriate nutrition care plan (FANTA, 2016)

2.4 MEASURES OF NUTRITIONAL ASSESSMENT

There are four generally accepted measures of nutritional assessment; anthropometric assessment, biochemical or laboratory assessment, clinical or physical assessment and dietary assessment. These are often referred to as ABCD of nutritional assessment.

2.4.1 ANTHROPOMETRIC ASSESSMENT: The word anthropometry is derived from two words "anthropo" meaning "human" and "metric" meaning "measurement". Its measures include body height or length, weight, skinfold thickness and body circumferences (arm, hip, waist and head). These measures of anthropometry provide an objective measure of body muscle, bone and fat to assess either body growth or changes in body composition.

There are two major sources of anthropometric information in Nigeria; Multiple Indicator Cluster Surveys (MICS) and National Demographic and Health Surveys (NDHS). Anthropometric information data collection methodologies include; repeated surveys (either national or small-scale surveys), growth monitoring (either clinic-based or community-based monitoring), sentinel site surveillance (either centrally-based or community-based sentinel site surveillance) and school census data (FAO, 2007).

Anthropometric indices such as weight-for-height, height-for-age, weight-for-age, Body Mass Index (BMI), Mid-Upper Arm Circumference (MUAC), and head circumference are used for assessing body growth, whereas skinfold thickness, ultrasound, Dual X-Ray Absorptiometry

(DXA), Magnetic Resonance Imaging (MRI) and Bioelectrical Impedance Analysis (BIA) are used in assessing body composition (Subramanian, Corsi and Subramanyam 2011).

2.4.2 BIOCHEMICAL OR LABORATORY ASSESSMENT: Biochemical or laboratory assessment of nutritional status involves laboratory test carried out on blood, urine, hair and nail samples of an individual (Maqbool *et al,* 2014). Biochemical nutritional assessment indices include; serum retinol, haemoglobin count, urinary iodine, serum zinc, and serum B12 (Subramanian, Corsi and Subramanyam 2011).

2.4.3 CLINICAL OR PHYSICAL ASSESSMENT: This involves checking for physical signs of nutritional deficiencies on any part of the body such as on the hair, face, eyes, lips and tongue and asking questions on symptoms attributable to nutrient deficiency (Upadhyay and Tripathi, 2017). Clinical assessment of nutritional status in children involves checking for signs such as bilateral pitting oedema, severe wasting, inability to gain weight and ineffective breastfeeding (FANTA, 2016)

2.4.4 DIETARY ASSESSMENT: Dietary assessment of nutritional status involves the quantification of what people eat by using any of the dietary intake indicators. It provides information on the amount, quality of food consumed, eating pattern and family behaviour, through the recording or statement of the number of meals, beverages consumed and supplement ingested regularly (Maqbool *et al,* 2014). The Dietary assessment also provides a means of identifying food patterns and preferences for individuals and groups of people.

2.5 CATEGORIZATION OF DIETARY ASSESSMENT

2.5.1 RETROSPECTIVE ASSESSMENT: This include; 24 hours recall, telephone recall, food frequency and semi-quantitative food frequency questionnaire and dietary history.

2.5.2 PROSPECTIVE ASSESSMENT: This include; weighed food record, food dairy and duplicate portion analysis

2.6 IMPORTANCE OF BMI AS A BETTER MEASURE OF UNDER-FIVE NUTRITIONAL STATUS

Body Mass Index (BMI) is an anthropometric index of measures of weight and height, defined as an individual's weight in kilograms divided by height in metres squared. Its choice over other anthropometric indices includes; its ease of measurement, long-age history of application and ability in predicting excellent disease risk. It also provides a measure for determining public health policies (Nuttall, 2015) and serves as an indicator for assessing adiposity in children (Freedman and Sherry, 2009).

2.7 ASSESSMENT OF UNDER-FIVE NUTRITIONAL STATUS

Globally, stunting among under-five children was estimated to be about 150.8 million representing 22.2% of the global under-five children in 2017. Across the world, there is a disparity in the distribution of this nutritional status of children. Stunting among under-five children or in childhood was estimated to be 83.6 million in Asia followed by 58.7 million in Africa and, at the least of 0.5 million in Oceania.

Health effects of stunting are devastating as it prevents children from attaining their likely attainable height and inability of their brain to develop full cognitive potential affecting significantly ease of learning and academic performance, this malnutrition can continue with a child till death and it is hereditary.

Though, the global burden of stunting has declined from 198.4 million in 2000 to 150.8 million in 2017, it was estimated that at least half of the global stunted children lived in Asia and at least 33% lived in Africa. Across the world's sub-regions, more than 25% children are stunted. With the prevalence of stunting highest in Asia and Africa, Southern Asia has the highest prevalence of 33.3% representing 58.7 million children in Asia, elsewhere, Eastern Africa showed the same feat as Southern Asia in Asia with 35.6% prevalence representing 23.9 million children (UNICEF, WHO, WB, 2018)

Overweight is used to refer to a phenomenon in childhood that defines a state of heavy body weight for a child's height, it is associated with over-nutrition. Childhood overweight is estimated to be 38 million representing 5.6% of the world's under-five population. The Burden of childhood overweight was estimated to be 17.5 million and 9.7 million in Asia and Africa respectively. Prevalence of childhood overweight increased from 4.9% in 2000 to 5.6% in 2017 equaling global burden of 30.1 million in 2000 to 38.3 million in 2017.

The burden of childhood overweight was estimated to be least and highest in Asia and Africa with a prevalence of 3.1% in Southern Asia and 10.7% in Central Asia and in Africa, 2.4% in West Africa and 13.7% in Southern Africa. Of the 17.5 million overweight children in Asia, 5.4 million lived in Southern Asia, whereas, in Africa with an estimated burden of 9.7 million, 3.0 million resides in Northern Africa (UNICEF, WHO, WB, 2018)

Across the globe, childhood wasting defined as acute malnutrition results from childhood disease and infection which causes inability to gain weight rapidly or weight loss. A wasted child generally refers to a child too lean compared to the child's height. An estimated 7.5% of the global children were wasted representing 50.5 million in 2017. Wasting results from poor dietary intake or infection. It causes poor immunity, ease of disease susceptibility and high risk of childhood mortality but could be prevented by urgent feeding. Prevalence of wasting increased from 4.9% in 2000 to 7.5% in 2017 representing 30.1 million in 2000 and 50.5 million in 2017 respectively. Two-third of children in Asia are wasted and at least 25% lived in Africa. In Africa, the prevalence of wasting was 8.1% in both Northern and Western Africa respectively. In Asia wasting was highest in Southern Asia with a prevalence of 15.3%. Of the 35.0 million estimated childhood wasting in Asia by 2017. Southern Asia has the highest burden of 26.9 million. Childhood wasting was estimated to be 13.8 million in Africa, of which 5.1 million lived in Western Africa in 2017 (UNICEF, WHO, WB, 2018).

In Nigeria, the under-five population has been projected to be at least 33.9 million by 2020 representing 16.46% of the nation's total population with more males (51.2%) than females (48.8%). There has been improvement in the childhood wasting and overweight from 13.4% in 2007 to 10.8% in 2016 and 13.3% in 2007 to 1.5% in 2016 respectively. Whereas the prevalence of stunting and underweight have increased from 39.2% in 2007 to 43.6% in 2016 and 23.3% in 2007 to 31.5% in 2016 respectively (MICS, 2016; 2007).

In the latest Global Nutrition Report (GNR, 2018) about 13.9 million and 3.4 million children were stunted and wasted respectively in Nigeria. Prevalence of childhood malnutrition is highest in North-Western Nigeria, while being a male child and living in rural area increases the likelihood of being malnourished (USAID, 2018). Also, National Nutrition and Health Survey (NNHS) 2018 estimated underweight (19.9%), stunting (32.0%), overweight (1.2%), wasting was between (5 – 9.9%) (NNHS, 2018).

Study within the country has revealed varying patterns among children as reported by Okari, Nte and Frank-Briggs (2019) in a cross-sectional descriptive study of 410 children at Okrika town determined the prevalence of malnutrition among under-five children and showed that 13.6%, 8.8% and 10.5% of these children were stunted, wasted and underweight respectively.

Akorede and Abiola (2013) in a study of 355 participants that assessed the nutritional status of under-five children in Akure South LGA showed that 12.5%, 14.8 % and 8.5% of these children were stunted, wasted and underweight respectively, while some of children showed signs of malnutrition. Their results have shown that stunting and underweight still remains a major nutritional problem among Nigerian children.

2.8 FACTORS INFLUENCING NUTRITIONAL STATUS OF UNDER-FIVE CHILDREN IN NIGERIA

Several studies have explored factors associated with the nutritional status of children. These factors include:

2.8.1 AGE OF THE CHILD

Malnutrition in under-five children has shown to be increasing with ages in both males and females till the age of three years followed by a decrease as the child grows (Kabeta, Belagavi and Gizachew, 2017). This was in harmony with the study conducted in Kenya, revealing a peak age of three years, risk factors such as inadequate weaning culture, unhealthy environmental conditions, poverty and immunization factors have been identified to this age of undernutrition (Nungo, Okoth and Mbugua, 2012).

But the peak age reported by Amadi *et al* (2018) was four years, showing that undernutrition is more prevalent in older children, with the supportive statement that growth and development were mild from infancy but became revealing in their later age. Acquah *et al,* (2018) reported that children aged 12 – 23 months had the highest likelihood of been malnourished as this could be attributed to their enthusiasm towards walking and freedom demanding more energy from them. Hein and Kam (2008) attributed high malnutrition in the children age group 12 – 23 months to inappropriate feeding alternative during weaning of the children against breastfeeding. A report by USAID (2018) on Nigeria's nutrition profile recorded a peak age of 24 – 35 months.

2.8.2 MOTHER'S LEVEL OF EDUCATION

A higher level of maternal education has been profound to be a significant factor in children's nutritional status. Studies have also shown that higher maternal educational level yields efficiency in the management of limited resources, better utilization of health care services, better health practices and more child-oriented care all of which guards against adverse child health condition (Hein and Kam 2008).

Acquah *et al* (2019) revealed that educated mothers embrace good child health care, feeding and eating practices which help to improve their children's nutritional status.

Maternal level of education is a significant factor affecting child's health status (Bhandari and Chhetri, 2013) as those whose highest education was at least junior high school was more associated with children's malnutrition compared with those who completed primary school or lesser (Hein and Kam 2008)

2.8.3 PARENT'S WEALTH STATUS

Parent's wealth status is determined by their level of education, type of occupation, ownership of assets, though this does not translate to proportional food intake for the family neither does the constant supply of food guarantee balanced diet, sufficient resources availability to a household opportune it a better purchasing power to get quality and nourishing food for their family (Girma and Genebo 2002).

Acquah *et al* (2019) reported a significant relationship between childhood malnutrition and parent's wealth status, children from the richest wealth status were less likely to be malnourished compared to their peers from the poorest wealth status. This was reinforced by Ruwali (2011), saying that socio-economic status is the most significant factor associated with children's nutritional status as children from low socio-economic status are highly malnourished compared to children from high socio-economic status. Beka *et al* (2009) revealed that in the urban area, children from rich socio-economic status are well-nourished than their peers from poor socio-economic status. Hein and Kam (2008) reported a relationship between low socio-economic status and increased number of child birth.

2.8.4 LOCATION OF RESIDENCE

A comparative study into the nutritional status of both rural and urban under-five children showed that there was no statistical significance between both dietary intake but the level of undernutrition was higher in rural area compared to urban area (Senbanjo *et al,* 2016; Oninla *et al,* 2006), they both concluded that inappropriate and lack of food was not a key factor to this discrepancy.

Elullu and colleagues (2014) reported that the effect of urbanization, low physical activities and increased medical provisions placed the urban area at the low impact of undernutrition than overnutrition compared to the rural area.

Amadi *et al* (2018) reported that higher prevalence of undernutrition is more attributed to the rural area than the urban area. Bhandari and Chhetri (2013) reported that residency in an urban area provides a protective measure against adverse nutritional status with a significant effect.

Hein and Kam (2008) attributed rural area's poor nutritional status to economic differences, cultural and social welfarism resulting in poor access to education and healthcare services.

2.8.5 GEOGRAPHICAL REGION

The northern region has been characterized with high temperature and a longer period of the dry season as compared to the southern region, has a higher proportion of underweight children USAID (2018). The northern region recorded the highest underweight prevalence of 19.8% in under-five children, making the northern region is 1.39 times more likely to be underweight in comparison to the western region age-group (Acquah *et al,* 2019).

2.8.6 GENDER

The long-aged practice African culture has placed the male child in better care and nutritional benefit that have led to a predominance of undernutrition in female counterparts (Acquah *et al,* 2019). (Ahmad, Khalil and Khan, 2011) found out that the same result in India, and concluded that it was a societal custom adversely impacting the female child.

Contrary, to this was the findings by Nungo, Okoth and Mbugua (2012) in Kenya which revealed that the male children were more undernourished compared to their female counterparts without any justification for this finding. Hein and Kam (2008) reported that the prevalence of malnutrition was higher in males compared to females and that this nutritional deficiency was due to environmental stress. Ruwali (2011) reported that the nutritional status of under-five children was not statistically significant between both male and female.

2.8.7 HOUSEHOLD SIZE

This is the number of individuals in a family. Hein and Kam (2008) found that large household size was a protective factor against malnutrition in children. Increase in household size accompanied by a decrease in per capital income has an adverse effect on children's nutritional status as a result of reduced food allocation (Chaudhury *et al,* 2009)

2.9 LITERATURE REVIEWS ON THE APPLICATION OF QUANTILE REGRESSION

Austin and Schull (2003), conducted a study on 10,584 out-of-patients with chest pain, the 90th conditional quantile regression model was compared with the conditional mean regression model. The study revealed that the following unique criteria for use of quantile regression (i) increment of regression slope line with increasing quantile (ii) non-uniformity space between regression lines and regression lines spacing widen with increasing quantile and (iii) the conditional mean estimate is greater than the median or 50th conditional quantile regression estimate. It was further reported that more exploration should be given to significance report of the 90th conditional quantile regression than the conditional mean regression. They concluded that the traditional regression models and univariate statistics are of limited use when analysing out-of-hospital care characteristics.

Cavrini (2010) in a study aimed to propose a new methodology for modelling the EQ-5D index and EQ-5D VAS in explaining lifestyle determinants, a random sample of 1622 adults aged 18 years and above were randomly selected using a cross-sectional study design. It was reported that quantile regression was preferred to the traditional linear regression due to the non-normality of the distribution of the EQ-5D and EQ-5D VAS; age, gender and comorbidity were found to explain variability in participants perceived health status.

In a cross-sectional study design involving 494 adolescents aged 10 – 17 years from 909 households in Rivers state, Nigeria, with the aim of investigating their nutritional status, the study was analysed by fitting quantile regression model which showed that age, sex, food insecurity and household economy were determinants of nutritional status assessed by their BMI, of which the distribution of BMI was 39%, 49.8%, 5.5% and 6.1% for underweight, normal weight, overweight and obese respectively. (Yusuf *et al*, 2017)

2.10 FACTORS INFLUENCING THE NUTRITIONAL STATUS OF UNDER-FIVE CHILDREN

Following the review of variables available in the MICS – 5 datasets for under-five children and the UNICEF (1998) conceptual framework for children nutritional status, Figure 2.1 is adopted to analyse childhood nutritional status. This examines biological and socioeconomic underlying factors such as age and gender of the child, mother's level of education, parent's wealth status, and household size. Effects of basic factors such as the location of residence and the geopolitical region were examined.

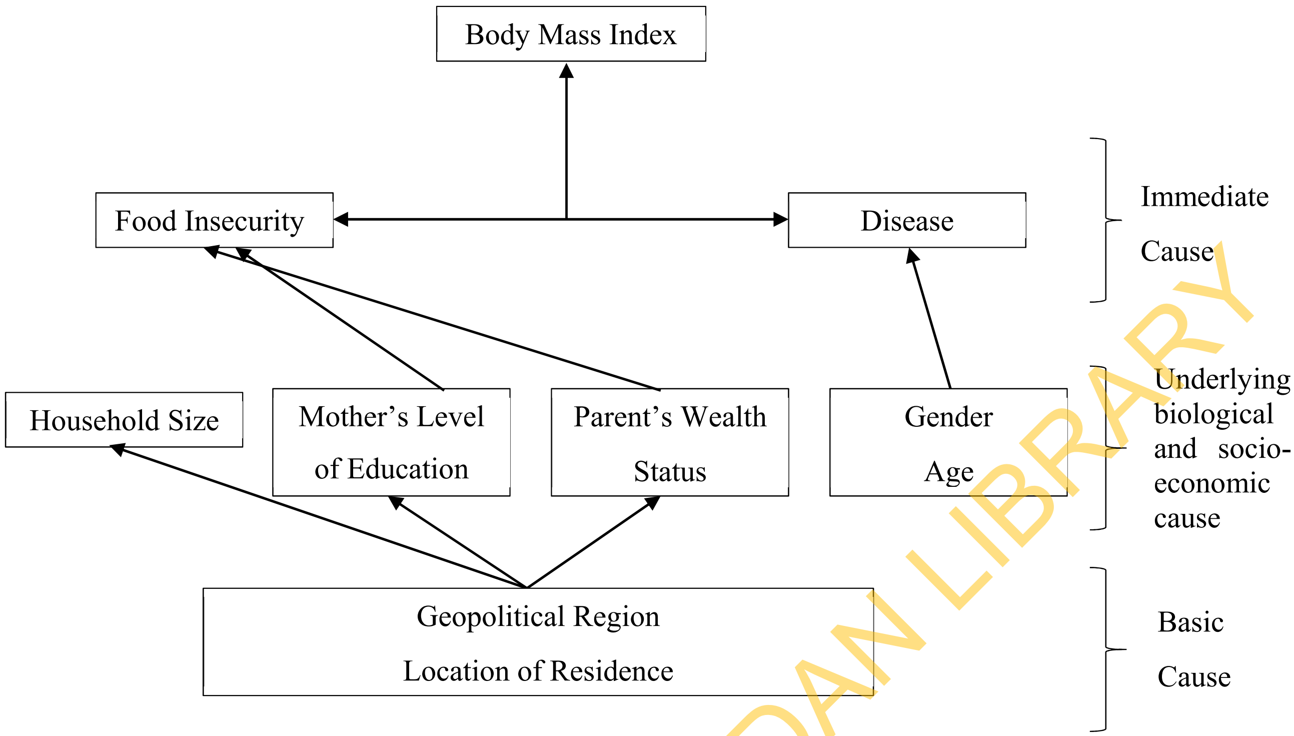

Figure 2.1: Conceptual framework of factors influencing nutritional status of under-five children.

Source: UNICEF 1998

CHAPTER THREE

3.0 METHODOLOGY

3.1 STUDY AREA

Nigeria is a country located in the western part of the Africa continent; it doubles as one of the Sub-Saharan African nations. She was formerly called the Royal Niger Company Territories but current name was coined from the word "Niger Area" by Flora Louise Shaw who later married Sir Fredrick Lord Lugard, Nigeria's colonial administrator. Nigeria witnessed the amalgamation of the Northern protectorate and Southern protectorate in 1914. Nigeria gained her independence from the British colonial masters on 1st of October, 1960 and became a federal republic on October 1st, 1963 as the Federal Republic of Nigeria.

Nigeria has the highest population in Africa and a robust economy, earning her the title "Giant of Africa", she currently ranks seventh in world population statistics and with her current growth rate of 2.6% and total fertility rate of 5.4%, Nigeria is projected to be the world third most populated country by 2050 after India and China (UN, 2017). Most of her populace reside in the South and Southwestern region, with Lagos state located in the Southwestern region having the highest population in the country.

Nigeria is not a landlocked state, located on latitude 4^0N and 14^0N and longitude 2^0E and 15^0E, time zone GMT +1, has a total land area of 923,768 km^2, she ranks 32nd in the world and 14th in Africa. She is bordered in the North by the Republic of Niger, the Republic of Chad in the North East, the republic of Cameroon in the East, the Republic of Benin in the West and in the South, the Gulf of Guinea by an approximate 850 kilometres of the world second largest ocean, the Atlantic Ocean.

Nigeria is made up of thirty-six states and the Federal Capital Territory, her states are distributed within these six geopolitical zones: North West, North East, North Central, South

West, South East and South-South. South East has five states, South West, South-South and North East have six states, whereas North Central and North Central have seven states.

There are 774 local government areas in Nigeria, having two major religion groups; Islam and Christianity, with the Islam dominating the Northern region and the Christian the Southern region. Nigeria has more than 250 ethnic groups, with the major ones being the Hausas, the Ibos and the Yorubas accounting for almost 70% of the ethnicity in the country, others such as the Tivs, the Idomas are referred to as the minor ethnic groups.

3.2 STUDY DESIGN

The dataset for this study was extracted from the nationally representative survey of the Multiple Indicator Cluster Survey – round 5 (MICS5) 2016, which utilized a descriptive cross-sectional study design. It was carried out in collaboration with United Nations Children's Fund (UNICEF) by the National Bureau of Statistics (NBS), Nigeria, formerly called Federal Office of Statistics (FOS). MICS5 is the fifth of its kind, the first two rounds MICS1 and MICS2 were carried out in 1995 and 1999 respectively under the former name FOS, while starting from the third MICS3 in 2007, the fourth MICS4 in 2011 and this the MICS5 held between September 2016 and January 2017 were under the new name NBS. MICS primarily was targeted to gather data on considerate indicators regarding survival, development and safe-guarding of men, women and children.

3.3 STUDY POPULATION

The MICS5 – 2016 study population include women aged 15 – 49 years, men aged 15 – 49 years and children aged 0 – 59 months. Selection of Households (HHs) within Enumeration Areas (EAs) in the country provided representative samples studied from the target population, children's parents/care-givers provided information regarding their ward in addition to their anthropometrics taken. This study focuses on children aged 0 – 59 months, to explore factors influencing their nutritional status.

3.4 SAMPLING TECHNIQUE

The MICS5 – 2016 was carried out to give estimates for a large number of measures on status regarding children and women, it was conducted simultaneously with the National Immunization Coverage Survey (NICS) to provide estimates of vaccine coverage in the country. The study utilized a two-stage sampling technique. The states within the federation were the main sampling unit and the Enumeration Areas (EAs) within each state serves as the Primary Sampling Units (PSUs). The selection of the EAs was drawn from the National Integrated Survey of Households – round 2 (NISH2) main sample, derived from the frame of EAs used for the 2006 National Population Census.

The first stage of the two-stage sampling technique involves the selection of EAs, the PSU from each state, the main sampling strata; the second stage was the selection of households, the Secondary Sampling Unit (SSU) from selected EAs. Across the federation states, 60 EAs were systematically selected from the NISH2 main samples, except in Lagos and Kano state where 120 EAs were selected, this was to ensure disaggregation of indicators at district senatorial level, a request made by respective state government to have sufficient samples. 16 households (HHs) were systematically selected from each EAs after household listing activities was carried out in each EAs, stratification was done by state and not by self-weighting, of the 2340 EAs selected for the survey 2239 were covered during field exercise, 101 EAs were inaccessible due to insecurity that encamped them.

3.5 SAMPLE POPULATION

A total of 27,766 records consisting of 14,048 males and 13,718 females under-five children were analyzed for this study, this sample population was available for analysis after all cases with missing outcome variables and BMI values greater than 99.90kg/m^2 and records with missing observations were removed.

3.6 STUDY VARIABLES

The listed variables were used for this study

3.6.1 OUTCOME VARIABLE

The continuous measure of the BMI was the study outcome variable, using the anthropometry measures of height and weight.

3.6.2 INDEPENDENT VARIABLES

The independent variables included in this study were age (in months), sex, mother's level of education, area of residence, geopolitical region, parent's wealth status, household size. The description of the variables are presented in Table 3.1

Table 3.1: Variable Categorization of Study Participants

Variables	Category
Age (in months)	0 – 6
	7 – 11
	12 – 23
	24 – 35
	36 – 47
	48 – 59
Sex	Male
	Female
Location of Residence	Rural
	Urban
Mother's Level of Education	No formal education
	Primary education
	Secondary education
	Tertiary education
Geopolitical Region	South East
	South South
	South West
	North Central
	North East
	North West
Parent's Wealth Status	Poorest
	Poorer
	Middle
	Richer
	Richest
Household Size	1 – 4
	5 – 8
	> 8

3.7 DERIVATION OF PARENT'S WEALTH STATUS

The parent's wealth status was arrived at using various composite indicator of wealth, these include type of floor, roof, wall, fuel used by household for cooking, household assets, source and location of drinking water and sanitation facility. Principal components analysis was performed to generate factor weight for each of the items used. Beginning with initial factor weights generated for the total sample, then followed by separate weights for households in rural and urban areas and conclusively with rural and urban weights regressed on initial weights to obtain the combined final weight for the total sample. Household population was then ranked according to the wealth score, divided into five equal parts (quintiles) from lowest to richest (MICS 2016-17)

3.8 DATA MANAGEMENT

The nationally representative survey of MICS5 – 2016/17 under-five children was used for this study. Descriptive statistics of frequency tables and proportions were used to summarize categorical variables, median and inter-quartile range (IQR) for continuous variables, test of normality was performed on BMI and pseudo R^2 to measure model goodness of fit. Two hundred samples bootstrap method was carried out to estimate unbiased standard error of each estimated coefficients. The 95% confidence interval for each coefficient estimate was calculated from the standard error estimate of the bootstrap samples.

Quantile regression model was fitted using STATA syntax "qreg" and the quantile plots using STATA syntax "grqreg". These were analyzed using STATA version 12 (STATA Corp, 2011)

The relationship between the dependent variable and independent variables was analysed at the 0.05th, 0.10th, 0.25th, 0.50th, 0.75th, 0.85th, 0.90th and 0.95th conditional quantile of the outcome distribution (CDC, 2000).

3.9 QUANTILE REGRESSION

Quantile regression is a statistical methodology that offers a comprehensive and reflective analysis of the relationship between the response variable and associated predictor variable, this is portrayed through its estimation of conditional regression estimates at specific quantile of the outcome distribution. Quantile regression permits the effects of the covariates to vary across the full distribution of the outcome variable. It serves as an improvement to the linear regression model since it provides some insight about the distribution of the dependent variable outside its conditional central measure i.e., the conditional mean.

Quantile regression ability to measure the effects of independent variables at any point or quantile of the dependent variable distribution is of utmost requirement due to its inherent characteristics to describe the extreme lower and upper distribution of the outcome variable, in the state of the Body Mass Index (BMI) distribution is associated with the underweight and obesity respectively.

The quantile regression model as represented by its abridged matrix formula is given as

$$Y_i^p = X_i \beta_i^p + \varepsilon_i^p \qquad \text{eqn 3.1}$$

$$0 < p < 1$$

where, Y_i^p is the BMI of the p^{th} quantile, having a probability density function (pdf) of

$$F(y) = \text{prob}\ (Y \leq y)$$

Y is the (n by 1) matrix of the observed outcomes

X is the (n by k) matrix consisting of the observed vector X

$\beta^p = (\beta_1^p,...,\beta_k^p)$ is the unknown k-dimensional vector of the specified quantile parameters, and,

$\varepsilon = (\varepsilon_1,...,\varepsilon_n)$ is the n dimensional vector of unknown errors

3.9.1 ASSUMPTIONS:

1. The p[th] conditional quantile of $\varepsilon_i^p = 0$
2. The outcome variable is bounded and continuous.
3. Quantile Regression Model is heteroscedastic in nature i.e., the assumption of equal variance does not hold

3.9.2 METHOD OF PARAMETER ESTIMATION:

- Parameters are estimated by the minimization of the sum of weighted distances of the observed and expected/fitted outcome value.

3.9.3 ASSESSMENT OF QUANTILE REGRESSION MODEL GOODNESS OF FIT

Estimation criterion of the Quantile Regression Model is based on minimizing the sum of weighted distances $\sum_{i=1}^{n} d_i(y_i - \hat{y}_i)$, with estimation weights dependent on whether the observed values (y_i) is greater than the fitted value ($\hat{y}_i$) and vice versa.

Quantile Regression Model Goodness of Fit is estimated by comparing the sum of the weighted distances of the fitted model with the sum of the weighted distances of a null model i.e., model with no explanatory variable but only the constant or intercept term.

Considering the single-covariate quantile regression model, if R^I is the sum of the weighted distances for the single-covariate model and R^O is the sum of the weighted distance for the constant term model

$$R^{I} = \sum_{i=1}^{n} d_i(y_i, \hat{y}_i) = \sum_{y_i \geq \hat{y}_i} p\,|y_i - \hat{y}_i| + \sum_{y_i < \hat{y}_i} (1-p)\,|y_i - \hat{y}_i| \qquad \text{eqn 3.2}$$

and,

$$R^{O} = \sum_{i=1}^{n} d_i(y_i, \hat{Q}^{(p)}) = \sum_{y_i \geq \hat{y}_i} p\,|y_i - \hat{Q}^{(p)}| + \sum_{y_i < \hat{y}_i} (1-p)\,|y_i - \hat{Q}^{(p)}| \qquad \text{eqn 3.3}$$

where,

$$y_i = \beta_0^{(p)} + \beta_1^{(p)} x_i + \varepsilon_i$$

$$\hat{y}_i = \beta_0^{(p)} + \beta_1^{(p)} x_i$$

$$\hat{Q}^{(p)} = \beta_0^{(p)}$$

$$\text{Pseudo R-Squared} = 1 - \frac{R^{I}}{R^{O}} \qquad \text{eqn 3.4}$$

Since, R^I and R^O are not negative and R^I is never greater than R^O, Pseudo R-Squared lies between 0 and 1, with values closer to 1 indicating a better fit. This is a measure estimated at a specific quantile and not the whole distribution, it is referred to as the local measure of the quantile regression model at p^{th} quantile. This provides a measure of how well the covariates influences the examined quantile. Pseudo R-Squared can be utilized for determining model with the best goodness of fit for several nested models.

3.9.4 ESTIMATION OF QUANTILE REGRESSION MODEL STANDARD ERROR AND CONFIDENCE INTERVAL

There are basically two methods for estimating the standard error of the Quantile regression model; the standard large sample approximation or asymptotic approach and the bootstrap approach.

3.9.4.1 THE ASYMPTOTIC APPROACH: can be estimated either by the simpler and easier independently, and identically normally distributed (i.i.d.) model or the complex non-(i.i.d.) model. The asymptotic approach is characterized by complex procedures, due to skewness and outliers, these demerits make the utilization of the parametric assumption of the asymptotic approach inappropriate for estimating the standard error (Koenker, 1994).

3.9.4.2 THE BOOTSTRAP TECHNIQUE: offers a robust and practical approach that is independent of the probability density function of the outcome variable since it makes no assumption about the outcome variable's distribution. The bootstrap approach is defined as a technique for estimating the sampling distribution of parameter estimate calculated from a fixed and initial repeated sample of size n from a defined population.

Standard error estimate is derived from the standard deviation of the sample of the parameter estimated. Bootstrapping technique was introduced by Efron in 1979. Bootstrapping procedure includes drawing samples of the same size as the original sample size with replacement from the original dataset. With each resamples randomly departing from the original sample, where resamples have the same number of elements as the original sample but could contain more than one original data points while excluding other data points for subsequent resample.

Bootstrapping provides better inference for non-normally distributed data and utilized for data whose sampling distribution is difficult to evaluate. The bootstrap method can be estimated either by the large sample approximation to the variance of a specified conditional quantile $\hat{Q}^{(p)}$ or through the use of empirical quantiles of the estimated bootstrap.

3.9.5 ROBUSTNESS PROPERTY OF QUANTILE REGRESSION MODEL

Robustness is defined as lack of sensitivity to outliers and a state of model assumption violation with respect to the outcome variable. Outliers are values with high variability in relation to the general values. Robustness characteristics places Quantile Regression Model in a better position when investigating outcomes distribution that are highly skewed (Beyerlein *et al,* 2008).

This insensitivity to outlier is demonstrated through the modification of the outcome variable data point either above or below the quantile regression line without changing their relative positions i.e., estimates of both central and non-central quantiles remain unchanged with the introduction of an extreme value to either sides and not on the quantile regression line (Onyedikachi, 2015)

3.9.6 TRANSFORMATION AND EQUIVARIANCE PROPERTIES OF THE QUANTILE REGRESSION MODEL

Often in the analysis of a dependent variable, researchers and analysts manipulate models for better interpretation and to achieve a more efficient model fitting. Linear transformation of the dependent variable incorporates either the addition of a constant to the outcome variable (y) or its multiplication by a constant, for Quantile Regression, the conditional quantile can be linearly transformed thus as,

$$Q^{(p)}(c + ay|x) = c + a(Q^{(p)}[y|x]) \qquad \text{eqn 3.5}$$

provided "a" is positive, and

$$Q^{(p)}(c + ay|x) = c + a(Q^{(1-p)}[y|x]) \qquad \text{eqn 3.6}$$

when "a" is negative.

This is known as linear equivariance since the linear transformation is alike for the outcome variable and the conditional quantile. Essentially, this equivariance features of models and estimates is a phenomenon used to describe a state whereby if the data are transformed the models or estimates attract same transformation.

There are times when the distribution of the dependent variable is not normally distributed, that log transformation is used if it is in a state of positively skewed. Log transformation helps in modelling a predictor's effect in relative terms i.e., the predictor is observed as a multiplicative model rather than additive model. Log transformation preserves order, making it a member of the broad family of monotone transformation.

Generally, a transformation V is monotone if $V(y) < V(y^I)$ since $y < y^I$. This monotone equivariance properties fails in consideration of the Linear Regression Model i.e., for conditional mean but essentially characterize the Quantile Regression Model using their conditional quantile (Hao and Naiman, 2007).

For a monotone function V,

$$Q^{(p)}[V(y)|x] = \hat{V}[Q^{(p)}(y|x)] \qquad \text{eqn 3.7}$$

also, log of the conditional quantile of the outcome variable, y, is the same as the conditional quantile of $_{\log}y$,

$$\log[Q^{(p)}(y)|x] = Q^{(p)}[\log(y)|x] \qquad \text{eqn 3.8}$$

then, equivalently as,

$$Q^{(p)}(y|x) = e^{Q^{(p)}[\log(y)|x]} \qquad \text{eqn 3.9}$$

CHAPTER FOUR

4.0 RESULTS

4.1 DISTRIBUTION OF THE CHARACTERISTICS OF PARTICIPANTS

Table 4.1 shows the distribution of the characteristics of the participants. The distribution of all participants by characteristics showed that 21.0% was aged 36 – 47 months, 47.0% had mothers with no formal education and 34.0% lived in the North West geopolitical region.

The proportion of male children was slightly higher (50.6%) than female children (49.4%). More children (73.5%) lived in the rural areas compared to those in the urban areas (25.6%). The proportion of male and female children who lived in the rural areas was 72.9% and 74.1% respectively.

The proportion of male children aged 36 – 47 months was 21.1% whereas the proportion of female children aged 36 – 47 months was 21.2%. The proportion of male children whose mothers had no formal education was 47.2% whereas their female counterpart was 46.8%. The proportion of male and female children in the North West geopolitical region was 33.8% and 34.1% respectively.

The proportion of male children from the poorest wealth status was 22.3% whereas the proportion of female children from poorer wealth status was 22.5%. The distribution of household size revealed that household size of at least nine had the highest proportion of male children (51.4%) and female children (50.2%)

Table 4.1: Frequency Distribution of Participants by Sex

Characteristics	Male (N = 14048)	Female (N = 13718)	Total (N = 27766)
Age (Months)	**N (%)**	**N (%)**	**N (%)**
0 – 5	1366 (9.7)	1358 (9.9)	2724 (9.8)
6 – 11	1349 (9.6)	1333 (9.7)	2682 (9.7)
12 – 23	2716 (19.3)	2775 (20.2)	5491 (19.8)
24 – 35	2808 (20.0)	2600 (19.0)	5408 (19.5)
36 – 47	2945 (21.0)	2911 (21.2)	5856 (21.1)
48 – 59	2864 (20.4)	2741 (20.0)	5605 (20.2)
Area of Location			
Urban	3811 (27.1)	3557 (25.9)	7368 (26.5)
Rural	10237 (72.9)	10161 (74.1)	20398 (73.5)
Mother's Level of Education			
None	6570 (46.8)	6479 (47.2)	13049 (47.0)
Primary	2324 (16.5)	2289 (16.7)	4613 (16.6)
Secondary	4042 (28.8)	3859 (28.1)	7901 (28.5)
Tertiary	1112 (7.9)	1091 (8.0)	2203 (7.9)
Geopolitical Region			
South East	1188 (8.5)	1169 (8.5)	2357 (8.5)
South South	1596 (11.4)	1539 (11.2)	3135 (11.3)
South West	1451 (10.3)	1430 (10.4)	2881 (10.4)
North Central	2712 (19.3)	2564 (18.7)	5276 (19.0)
North East	2352 (16.7)	2335 (17.0)	4687 (16.9)
North West	4749 (33.8)	4681(34.1)	9430 (34.0)
Parent's Wealth Status			
Poorest	3138 (22.3)	3075 (22.4)	6213 (22.4)
Poorer	3093 (22.0)	3082 (22.5)	6175 (22.2)
Middle	2705 (19.3)	2639 (19.2)	5344 (19.2)
Richer	2634 (18.8)	2520 (18.4)	5154 (18.6)
Richest	2478 (18.8)	2402 (17.5)	4880 (17.6)
Household Size			
1 – 4	3375 (24.0)	3355 (24.5)	6730 (24.2)
5 – 8	3451 (24.6)	3471 (25.3)	6922 (24.9)
> 8	7222 (51.4)	6892 (50.2)	14114 (50.8)
Total	**14,048 (50.6%)**	**13,718 (49.4%)**	

4.2 CHARACTERISTICS OF THE PARTICIPANTS BY THEIR BMI.

Table 4.2 shows the distribution of the participants' characteristics by their BMI. The median BMI for all participants children aged 6 - 11 months had (15.60 $\pm$ 2.13), children whose mothers had no formal education had median BMI of (15.34 $\pm$ 1.92), and median BMI for children who lived in the North Central geopolitical region was (15.62 $\pm$ 1.92).

The median BMI of male children was slightly higher (15.44 $\pm$ 1.92) than the median BMI of female children (15.11 $\pm$ 1.91). Also, the median BMI of children form the rural areas (15.31 $\pm$ 1.91) was higher the median BMI of children from the urban areas (15.20 $\pm$ 1.90), whereas the median BMI of male and female children in the rural areas was (15.47 $\pm$ 1.95) and (15.14 $\pm$ 1.90) respectively.

The median BMI of male and female children aged 6 - 11 months was (15.81 $\pm$ 2.13) and (15.38 $\pm$ 2.09) respectively. The median BMI of male children whose mothers had no formal education was (15.50 $\pm$ 1.88), whereas their female counterpart was (15.13 $\pm$ 2.10). The median BMI of male and female children from the North Central geopolitical region was (15.62 $\pm$ 1.91) and (15.32 $\pm$ 1.92) respectively.

The male children from poorer wealth status had median BMI of (15.55 $\pm$ 2.02) which was higher than the median BMI of female children from poorer wealth status (15.23 $\pm$ 1.94). The median BMI of male and female children whose household size lies between five and eight was (15.47 $\pm$ 1.89) and (15.13 $\pm$ 1.91) respectively.

Table 4.2: Body Mass Index Distribution of Participants by Sex

Characteristics	Male	Female	Total
Age (Months)	**Median (IQR)**	**Median (IQR)**	**Median (IQR)**
0 – 5	15.41 (2.79)	14.88 (2.61)	15.12 (2.71)
6 – 11	15.81 (2.13)	15.38 (2.09)	15.60 (2.13)
12 – 23	15.44 (1.84)	15.09 (1.79)	15.24 (1.85)
24 – 35	15.68 (1.80)	15.33 (1.84)	15.53 (1.82)
36 – 47	15.54 (1.78)	15.21 (1.86)	15.38 (1.81)
48 – 59	15.05 (1.61)	14.78 (1.66)	14.92 (1.65)
Area of Location			
Urban	15.37 (1.86)	14.98 (1.94)	15.20 (1.90)
Rural	15.47 (1.95)	15.14 (1.90)	15.31 (1.91)
Mother's Level of Education			
None	15.42 (1.93)	15.12 (1.88)	15.27 (1.91)
Primary	15.50 (1.88)	15.13 (2.01)	15.34 (1.92)
Secondary	15.45 (1.93)	15.09 (1.89)	15.26 (1.91)
Tertiary	15.39 (1.86)	15.09 (1.93)	15.24 (1.94)
Geopolitical Region			
South East	15.38 (1.94)	15.05 (1.80)	15.22 (1.87)
South South	15.42 (1.77)	15.10 (1.85)	15.26 (1.82)
South West	15.36 (1.78)	14.92 (1.85)	15.16 (1.82)
North Central	15.62 (1.91)	15.32 (1.92)	15.48 (1.92)
North East	15.33 (1.98)	15.06 (1.87)	15.21 (1.93)
North West	15.45 (1.98)	15.10 (1.98)	15.27 (1.98)
Parent's Wealth Status			
Poorest	15.39 (1.94)	15.07 (1.88)	15.22 (1.89)
Poorer	15.55 (2.02)	15.23 (1.94)	15.40 (1.94)
Middle	15.49 (1.85)	15.22 (1.95)	15.36 (1.91)
Richer	15.42 (1.90)	15.04 (1.91)	15.24 (1.89)
Richest	15.34 (1.89)	14.98 (1.89)	15.17 (1.90)
Household Size			
1 – 4	15.46 (1.92)	15.12 (1.93)	15.28 (1.91)
5 – 8	15.47 (1.89)	15.13 (1.91)	15.30 (1.91)
> 8	15.43 (1.94)	15.09 (1.89)	15.26 (1.92)
Total	15.44 (1.92)	15.11 (1.91)	

4.3 DESCRIPTION AND TEST OF NORMALITY OF THE BMI DISTRIBUTION

Table 4.3 shows the descriptive characteristics and test of normality on BMI by participant's sex. The mean (SD) of the total sample, male and female participants was 15.37 (1.69), 15.52 (1.70) and 15.21 (1.66) respectively. Whereas, the median (IQR) was 15.28 (1.92) for the total sample, 15.44 (1.92) for the male children and 15.11 (1.91) for the female children. The Kolmogorov-Smirnov test of normality was significant with $p<0.0001$ for all participants, male and female children respectively.

Table 4.3: Descriptive Statistics and Test of Normality of Body Mass Index by Sex

	Mean	SD	Median	IQR	Min	Max	Skewness	Kurtosis	Test of Normality
Total Under-five Children	15.37	1.69	15.28	1.92	2.99	48.13	1.20	15.13	p<0.0001
Male Under-five Children	15.52	1.70	15.44	1.92	2.99	48.13	1.26	17.75	p<0.0001
Female Under-five Children	15.21	1.66	15.11	1.91	3.95	39.86	1.17	12.66	p<0.0001

4.4 QUANTILE REGRESSION COEFFICIENTS FOR ALL PARTICIPANTS

Table 4.4, shows the Quantile regression coefficients, standard errors and Pseudo R^2 of all participants BMI.

The ages 12 – 23, 36 – 47 and 48 – 59 months were associated with BMI across all the selected quantiles. Likewise, the differential effect of sex was associated with BMI across all the selected quantiles, the magnitude of the coefficients differed across the quantiles, these include, 0.23, 0.33 and 0.27 at the 5th, 85th and 95th quantiles respectively. Whereas, location of residence was not associated with BMI.

The primary and secondary educational statuses of mothers were associated with BMI at the upper quantiles. The mean differences in BMI between South South and South East were -0.12 and -0.30 at the 75th and 95th quantile respectively. Also, the mean difference in BMI between North East and South East, and between North West and South East were -0.19 and -0.14 at the 10th quantile respectively.

The mean differences in BMI between the poorer and the poorest were 0.07, 0.15, 0.13, and 0.13 at the 25th, 50th, 75th, and 85th quantiles respectively, whereas, the mean differences in BMI between the richest and the poorest were -0.12, -0.12, -0.18, and -0.19 at the 25th, 50th, 85th and 90th quantiles respectively. However, household size was not associated with BMI.

Table 4.4: Quantile Regression Coefficients and Standard Errors of All Participants for Selected Quantiles

Explanatory Variables	5th Quantile β (SE)	10th Quantile β (SE)	25th Quantile β (SE)	50th Quantile β (SE)	75th Quantile β (SE)	85th Quantile β (SE)	90th Quantile β (SE)	95th Quantile β (SE)
Age (months)								
0 – 5 C								
6 – 11	1.76(0.15)*	1.43(0.08)*	0.84(0.07)*	0.48(0.07)*	0.23(0.07)*	0.18(0.08)*	0.09(0.10)	-0.14(0.12)
12 – 23	1.67(0.14)*	1.26(0.07)*	0.62(0.06)*	0.14(0.06)*	-0.24(0.06)*	-0.36(0.07)*	-0.48(0.09)*	-0.63(0.12)*
24 – 35	1.92(0.14)*	1.55(0.07)*	0.89(0.06)*	0.38(0.05)*	0.03(0.06)	-0.11(0.07)	-0.31(0.09)*	-0.47(0.12)*
36 – 47	1.93(0.13)*	1.48(0.07)*	0.74(0.06)*	0.26(0.05)*	-0.13(0.05)*	-0.32(0.07)*	-0.44(0.09)*	-0.66(0.11)*
48 – 59	1.60(0.13)*	1.13(0.07)*	0.36(0.06)*	-0.22(0.05)*	-0.67(0.05)*	-0.86(0.07)*	-0.99(0.09)*	-1.20(0.11)*
Sex								
Female C								
Male	0.23(0.04)*	0.29(0.03)*	0.32(0.02)*	0.35(0.02)*	0.32(0.03)*	0.33(0.03)*	0.33(0.04)*	0.27(0.05)*
Location of Residence								
Rural C								
Urban	-0.06(0.05)	-0.06(0.04)	-0.04(0.03)	-0.06(0.03)	-0.05(0.04)	-0.08(0.04)	-0.05(0.05)	-0.04(0.07)
Mother's Level of Education								
No formal education C								
Primary education	0.02(0.06)	0.02(0.05)	0.07(0.04)*	0.08(0.04)*	0.15(0.04)*	0.18(0.05)*	0.12(0.06)*	0.22(0.08)*
Secondary education	-0.01(0.05)	0.02(0.05)	0.05(0.03)	0.09(0.04)*	0.14(0.04)*	0.20(0.06)*	0.17(0.06)*	0.21(0.09)*
Tertiary education	0.03(0.08)	-0.02(0.07)	0.07(0.05)	0.17(0.05)*	0.18(0.06)*	0.27(0.08)*	0.20(0.10)	0.30(0.13)*
Geopolitical Region								
South East C								
South South	0.02(0.09)	-0.04(0.06)	0.04(0.05)	0.05(0.04)	-0.01(0.06)	-0.01(0.08)	-0.13(0.11)	-0.14(0.11)
South West	0.06(0.09)	-0.02(0.06)	-0.02(0.04)	0.00(0.05)	-0.12(0.05)*	-0.11(0.08)	-0.17(0.11)	-0.30(0.12)*
North Central	0.17(0.09)	0.16(0.06)*	0.19(0.04)*	0.24(0.04)*	0.25(0.05)*	0.23(0.07)*	0.17(0.11)	0.12(0.11)
North East	-0.25(0.10)	-0.19(0.07)*	-0.04(0.04)	-0.00(0.04)	0.04(0.05)	0.11(0.08)	0.05(0.11)	0.08(0.12)
North West	-0.14(0.09)	-0.14(0.06)*	-0.07(0.04)	0.07(0.04)	0.08(0.05)	0.13(0.07)	0.04(0.10)	0.03(0.11)

* $p<0.05$ C = Reference Group SE = Bootstrapped Standard Error of 200 Resamples

Table 4.4 (Cont'd): Quantile Regression Coefficients and Standard Errors of All Participants for Selected Quantiles

Explanatory Variables	5th Quantile β (SE)	10th Quantile β (SE)	25th Quantile β (SE)	50th Quantile β (SE)	75th Quantile β (SE)	85th Quantile β (SE)	90th Quantile β (SE)	95th Quantile β (SE)
Parent's Wealth Status								
Poorest[C]								
Poorer	0.07(0.06)	0.03(0.05)	0.07(0.03)*	0.15(0.04)*	0.13(0.04)*	0.13(0.05)*	0.09(0.05)	0.04(0.08)
Middle	0.22(0.07)*	0.13(0.06)*	0.05(0.04)	0.08(0.04)*	0.05(0.04)	-0.00(0.06)	-0.00(0.06)	-0.06(0.10)
Richer	0.17(0.08)*	0.02(0.06)	-0.08(0.04)*	-0.05(0.04)	-0.07(0.05)	-0.10(0.06)	-0.13(0.07)	-0.20(0.11)
Richest	0.05(0.08)	-0.00(0.07)	-0.12(0.05)*	-0.12(0.05)*	-0.10(0.0)	-0.18(0.07)*	-0.19(0.08)*	-0.21(0.13)
Household Size								
1 – 4[C]								
5 – 8	-0.03(0.05)	-0.00(0.04)	0.01(0.03)	0.02(0.03)	0.02(0.06)	-0.02(0.04)	0.03(0.05)	-0.00(0.07)
> 8	-0.03(0.05)	-0.02(0.04)	-0.03(0.03)	-0.03(0.02)	-0.02(0.04)	-0.01(0.04)	-0.01(0.05)	-0.03(0.06)
Constant	11.24(0.17)*	12.19(0.09)*	13.61(0.07)*	14.84(0.07)*	16.16(0.07)*	16.82(0.11)*	17.47(0.14)*	18.41(0.16)*
5th Quantile Pseudo R^2	0.06							
10th Quantile Pseudo R^2	0.04							
25th Quantile Pseudo R^2	0.03							
50th Quantile Pseudo R^2	0.02							
75th Quantile Pseudo R^2	0.03							
85th Quantile Pseudo R^2	0.03							
90th Quantile Pseudo R^2	0.02							
95th Quantile Pseudo R^2	0.02							

* $p<0.05$ C = Reference Group SE = Bootstrapped Standard Error of 200 Resamples

4.5 DESCRIPTION OF THE QUANTILE PLOTS

Figure 4.1 – 4.22, show the Quantile Plots for various coefficients in the Quantile Regression Model for all participants. The thick line represents the quantile regression line with the shaded area around it representing its 95% confidence interval. Plotted on the quantile regression plot is a dashed line representing the Ordinary Least Squares (OLS) estimate of the mean effect and the dotted line above and below the dashed line representing its 95% confidence interval.

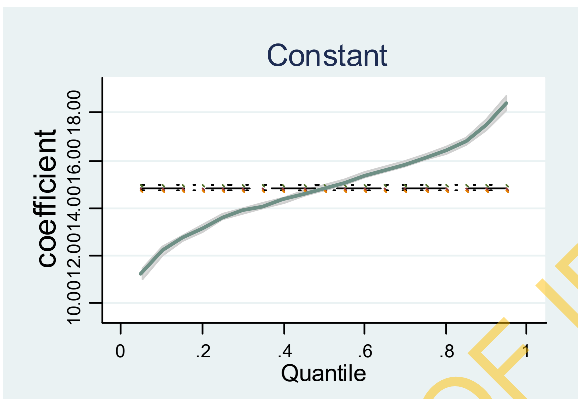

Figure 4.1: Quantile plot for Quantile Regression Model for the constant term

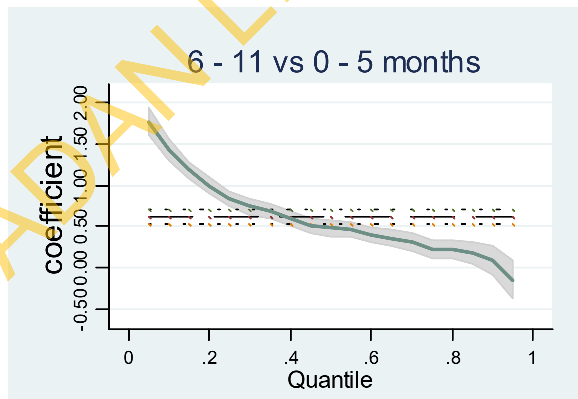

Figure 4.2: Quantile plot comparing Ages 6 – 11 against 0 – 5 months

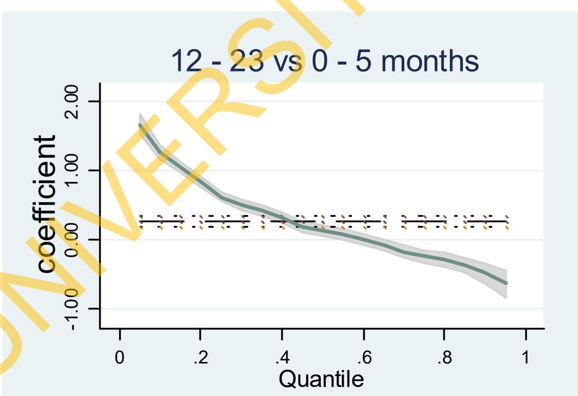

Figure 4.3: Quantile plot comparing Ages 12 – 23 against 0 – 5 months

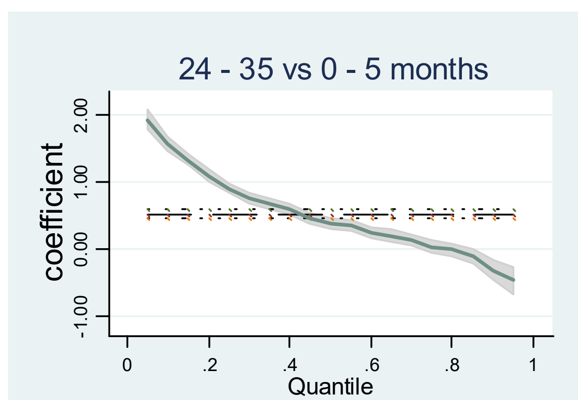

Figure 4.4: Quantile plot comparing Ages 24 – 35 against 0 – 5 months

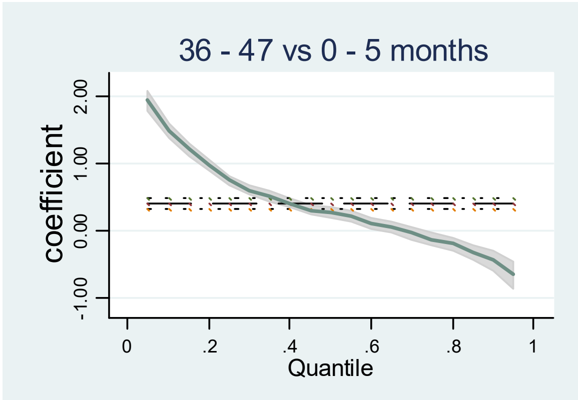

Figure 4.5: Quantile plot comparing

Ages 36 – 47 against 0 – 5 months

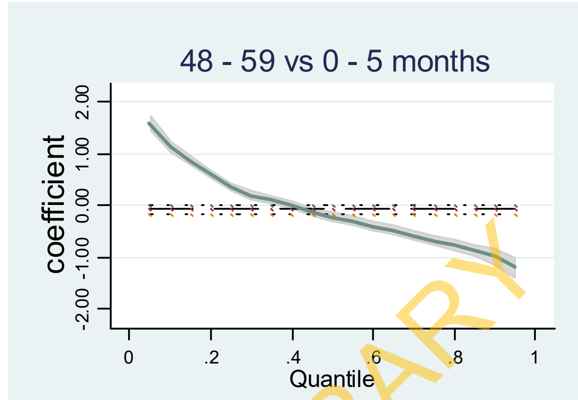

Figure 4.6: Quantile plot comparing

Ages 48 – 59 against 0 – 5 months

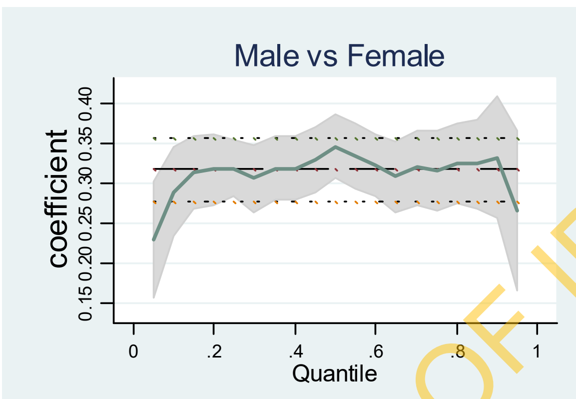

Figure 4.7: Quantile plot comparing

Male against Female

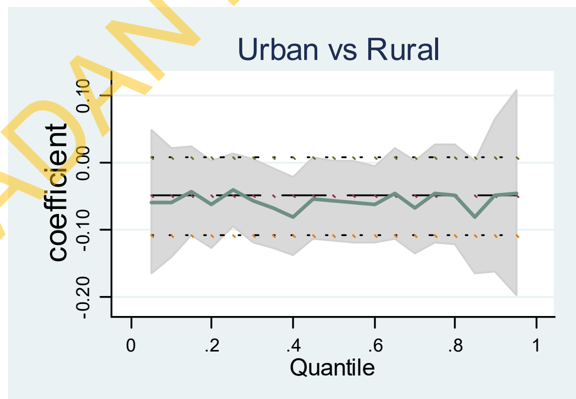

Figure 4.8: Quantile plot comparing

Urban against Rural

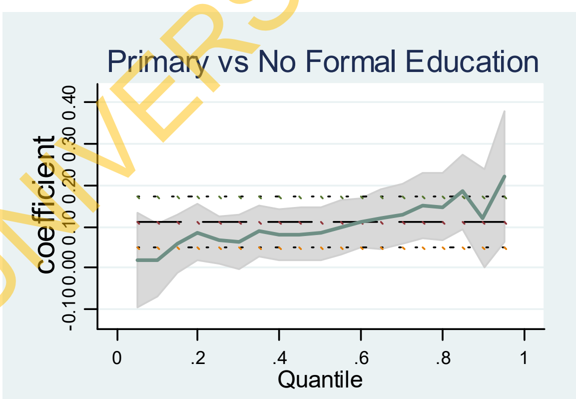

Figure 4.9: Quantile plot comparing

Mothers with Primary against No Formal Education

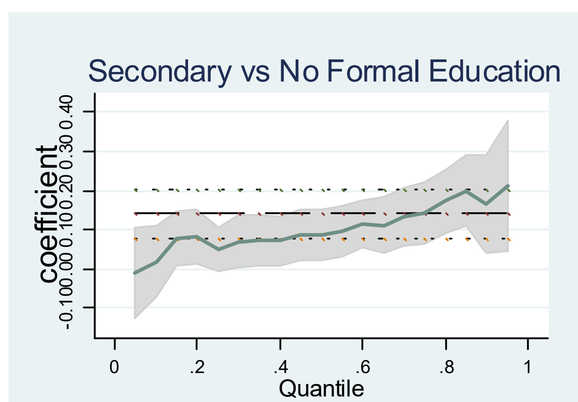

Figure 4.10: Quantile plot comparing

Mothers with Secondary against No Formal Education

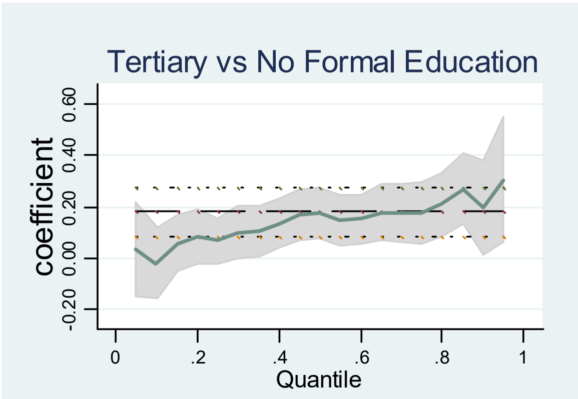

Figure 4.11: Quantile plot comparing

Mothers with Tertiary against No Formal Education

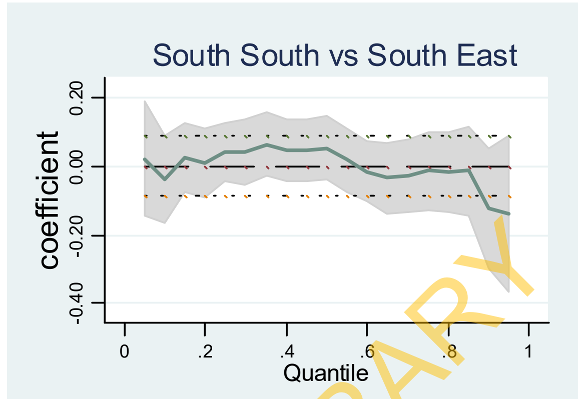

Figure 4.12: Quantile plot comparing

South South against South East

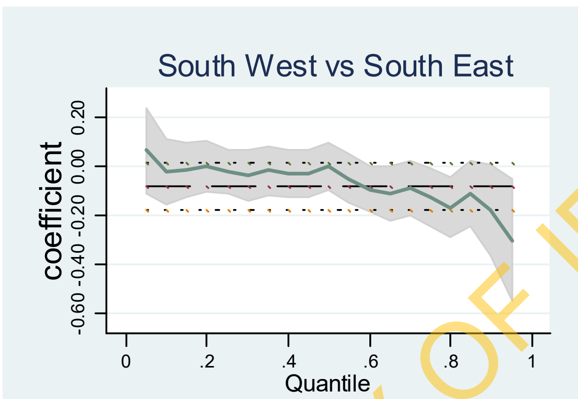

Figure 4.13: Quantile plot comparing

South West against South East

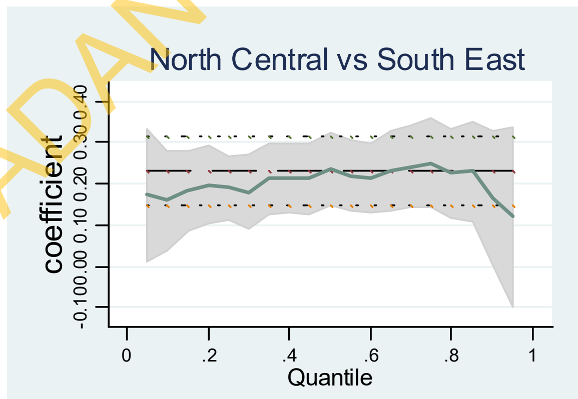

Figure 4.14: Quantile plot comparing

North Central against South East

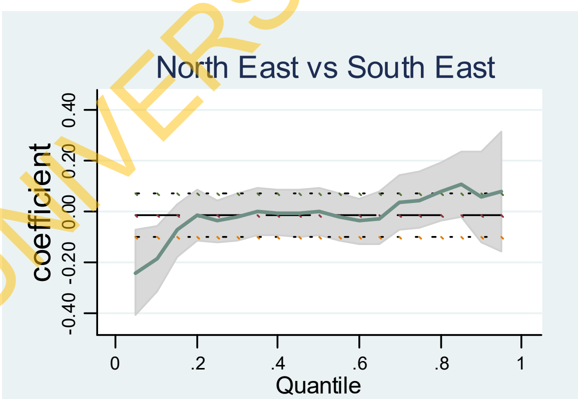

Figure 4.15: Quantile plot comparing

North East against South East

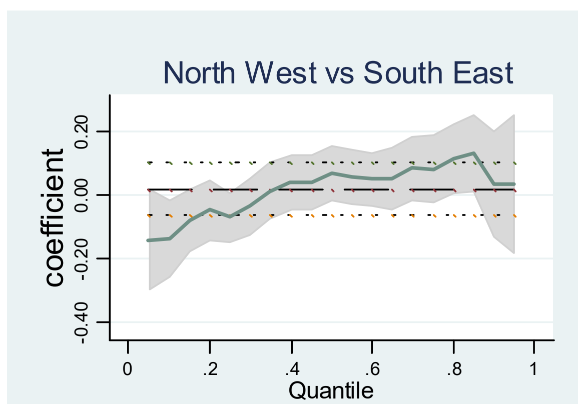

Figure 4.16: Quantile plot comparing

North West against South East

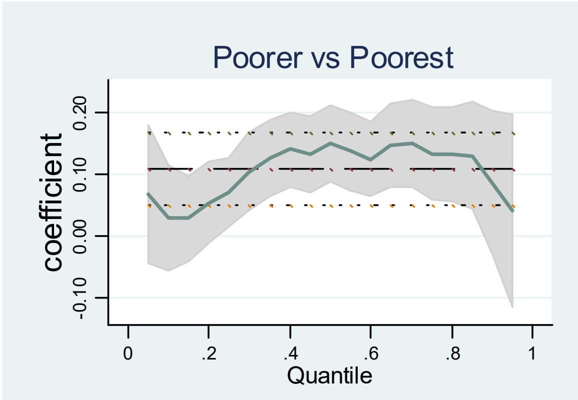

Figure 4.17: Quantile plot comparing Poorer against Poorest Wealth Status

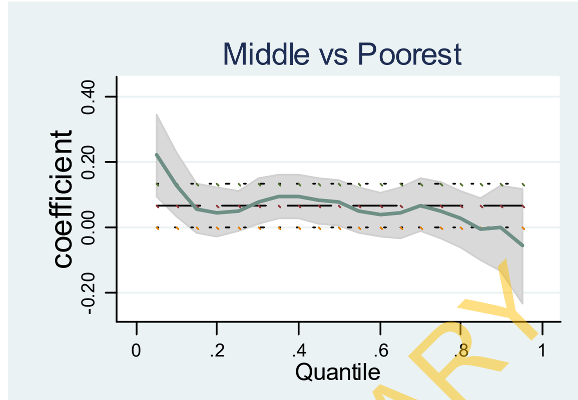

Figure 4.18: Quantile plot comparing Middle against Poorest Wealth Status

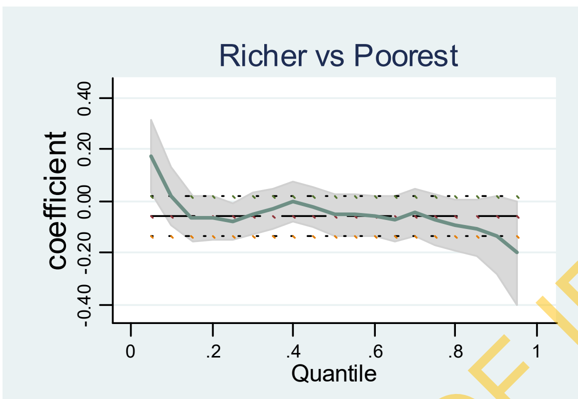

Figure 4.19: Quantile plot comparing Richer against Poorest Wealth Status

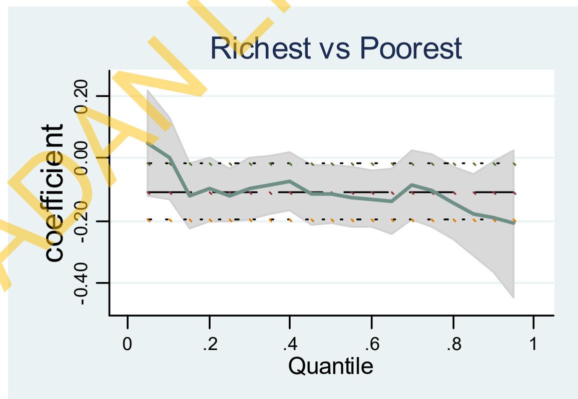

Figure 4.20: Quantile plot comparing Richest against Poorest Wealth Status

Figure 4.21: Quantile plot comparing 5 – 8 against 1 – 4 Household size

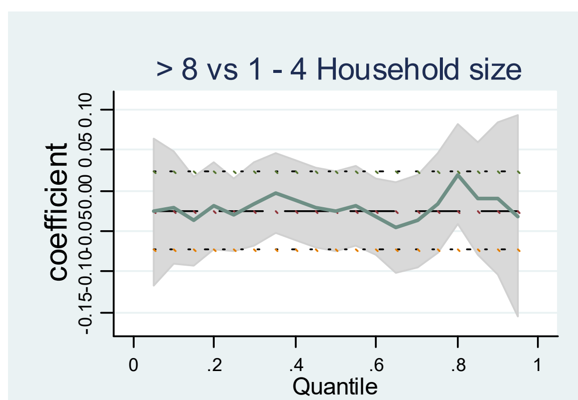

Figure 4.22: Quantile plot comparing > 8 against 1 – 4 Household size

4.6 QUANTILE REGRESSION COEFFICIENTS FOR MALE CHILDREN

Table 4.5, shows the Quantile regression coefficients, standard errors and Pseudo R^2 of the male children BMI.

The ages 48 – 59 months was associated with BMI across all the selected quantiles, whereas, the ages 6 – 11, and 24 – 35 months was associated with BMI at the lower quantiles. The mean difference in BMI between the urban and the rural area was -0.13 at the 85th quantile.

The mean difference in BMI between the secondary and no formal educational status of mothers was associated with BMI at the upper quantiles, i.e., BMI increased by 0.12, 0.16, 0.20, and 0.26 at the 75th, 85th, 90th, and 95th quantiles respectively.

The mean difference in BMI between South South and South East was -0.26 at the 90th quantile. Also, the mean difference in BMI between North West and South East was -0.22 at the 10th quantile.

The mean difference in BMI between the poorer and the poorest was 0.13 and 0.12 at the 50th and 85th quantiles respectively. Also, the mean difference in BMI between the richer and the poorest was -0.19 at the 90th quantile. Household size was not associated with BMI.

Table 4.5: Quantile Regression Coefficients and Standard Errors of Male Children for Selected Quantiles

Explanatory Variables	5th Quantile β (SE)	10th Quantile β (SE)	25th Quantile β (SE)	50th Quantile β (SE)	75th Quantile β (SE)	85th Quantile β (SE)	90th Quantile β (SE)	95th Quantile β (SE)
Age (months)								
0 – 5 C								
6 – 11	1.83(0.20)*	1.51(0.14)*	0.84(0.11)*	0.44(0.09)*	0.16(0.10)	0.04(0.15)	-0.02(0.16)	-0.26(0.21)
12 – 23	1.62(0.19)*	1.28(0.13)*	0.57(0.10)*	0.04(0.08)	-0.37(0.09)*	-0.56(0.12)*	-0.68(0.13)*	-0.91(0.18)*
24 – 35	1.79(0.19)*	1.51(0.13)*	0.86(0.10)*	0.27(0.08)*	-0.11(0.09)	-0.32(0.12)*	-0.52(0.13)*	-0.68(0.18)*
36 – 47	1.87(0.19)*	1.49(0.13)*	0.73(0.10)*	0.14(0.08)	-0.28(0.09)*	-0.54(0.12)*	-0.71(0.13)*	-0.93(0.18)*
48 – 59	1.53(0.18)*	1.08(0.13)*	0.29(0.10)*	-0.39(0.08)*	-0.85(0.09)*	-1.10(0.12)*	-1.23(0.13)*	-1.43(0.18)*
Location of Residence								
Rural C								
Urban	-0.01(0.07)	0.03(0.06)	-0.04(0.04)	-0.05(0.04)	-0.08(0.05)	-0.13(0.06)*	-0.04(0.09)	-0.03(0.11)
Mother's Level of Education								
No formal education C								
Primary education	0.09(0.08)	0.05(0.07)	0.09(0.04)*	0.10(0.05)*	0.13(0.07)	0.16(0.07)*	0.15(0.07)*	0.24(0.13)
Secondary education	0.06(0.08)	-0.02(0.07)	0.00(0.05)	0.09(0.05)	0.12(0.06)*	0.16(0.06)*	0.20(0.07)*	0.26(0.12)*
Tertiary education	0.13(0.12)	-0.07(0.11)	-0.00(0.08)	0.13(0.07)	0.10(0.09)	0.18(0.10)	0.12(0.13)	0.21(0.20)
Geopolitical Region								
South East C								
South South	-0.00(0.14)	-0.08(0.08)	0.05(0.07)	0.05(0.07)	-0.11(0.08)	-0.13(0.10)	-0.26(0.12)*	-0.28(0.17)
South West	0.11(0.15)	0.00(0.09)	0.05(0.06)	0.00(0.08)	-0.13(0.08)	-0.10(0.13)	-0.21(0.14)	-0.32(0.19)
North Central	0.10(0.14)	0.08(0.08)	0.19(0.06)*	0.24(0.06)*	0.17(0.08)*	0.15(0.10)	0.01(0.11)	0.03(0.18)
North East	-0.36(0.14)*	-0.35(0.10)*	-0.05(0.06)	-0.02(0.07)	-0.02(0.09)	0.07(0.11)	-0.01(0.13)	0.07(0.20)
North West	-0.19(0.14)	-0.22(0.09)*	-0.05(0.06)	0.07(0.06)	0.05(0.08)	0.05(0.10)	-0.12(0.11)	-0.04(0.17)

* $p<0.05$ C = Reference Group SE = Bootstrapped Standard Error of 200 Resamples

Table 4.5 (Cont'd): Quantile Regression Coefficients and Standard Errors of Male Children for Selected Quantiles

Explanatory Variables	5th Quantile β (SE)	10th Quantile β (SE)	25th Quantile β (SE)	50th Quantile β (SE)	75th Quantile β (SE)	85th Quantile β (SE)	90th Quantile β (SE)	95th Quantile β (SE)
Parent's Wealth Status								
Poorest[C]								
Poorer	-0.04(0.09)	-0.05(0.08)	0.02(0.05)	0.13(0.05)*	0.12(0.06)	0.12(0.06)*	0.08(0.07)	0.03(0.13)
Middle	0.12(0.10)	0.07(0.08)	0.07(0.05)	0.06(0.05)	-0.00(0.06)	-0.04(0.07)	-0.09(0.09)	-0.18(0.15)
Richer	0.11(0.11)	-0.04(0.09)	-0.04(0.05)	0.00(0.06)	-0.04(0.06)	-0.07(0.08)	-0.19(0.10)*	-0.18(0.17)
Richest	-0.12(0.13)	-0.10(0.10)	-0.08(0.06)	-0.07(0.07)	-0.06(0.08)	-0.14(0.09)	-0.23(0.14)	-0.21(0.21)
Household Size								
1 – 4[C]								
5 – 8	-0.05(0.07)	-0.02(0.06)	0.02(0.04)	0.04(0.05)	0.04(0.05)	0.01(0.06)	-0.04(0.08)	0.02(0.11)
> 8	-0.04(0.07)	-0.03(0.05)	-0.01(0.03)	-0.00(0.04)	0.00(0.04)	0.04(0.05)	0.01(0.06)	0.04(0.09)
Constant	11.62(0.21)*	12.61(0.15)*	13.94(0.12)*	15.27(0.10)*	16.66(0.12)*	17.41(0.17)*	18.15(0.18)*	18.94(0.26)*
5th Quantile Pseudo R^2	0.05							
10th Quantile Pseudo R^2	0.04							
25th Quantile Pseudo R^2	0.02							
50th Quantile Pseudo R^2	0.02							
75th Quantile Pseudo R^2	0.02							
85th Quantile Pseudo R^2	0.03							
90th Quantile Pseudo R^2	0.03							
95th Quantile Pseudo R^2	0.03							

* $p<0.05$ C = Reference Group SE = Bootstrapped Standard Error of 200 Resamples

4.7 QUANTILE REGRESSION COEFFICIENTS FOR FEMALE CHILDREN

Table 4.6, shows the Quantile regression coefficients, standard errors and Pseudo R^2 of the female children BMI.

The ages 24 – 35, 36 – 47 was associated with BMI at the 5th, 10th, 25th, 50th, 75th, and 95th quantiles respectively. Also, the age 6 – 11 months was associated with BMI at the 5th, 10th, 25th, 50th, 75th, and 85th quantiles. The differential effect of location of residence was not associated with BMI.

The mean difference in BMI between primary and no formal education, and secondary and no formal education was associated with BMI at the 75th and 85th quantiles respectively, whereas, the mean difference in BMI between tertiary and no formal education was 0.17, 0.23, 0.33 and 0.32 at the 50th, 75th, 85th, and 90th quantiles respectively. The mean difference in BMI between North Central and South East was associated with BMI across all the selected quantiles, whereas, the mean difference in BMI between North West and South East was 0.23 at the 85th quantile.

The poorer wealth status was associated with BMI at the 25th, 50th, 75th, and 85th quantiles. Also, the mean difference in BMI between the richest and the poorest wealth status was -1.80 and -1.20 at the 75th and 85th quantiles respectively. However, the differential effect of household size was not associated with BMI.

Table 4.6: Quantile Regression Coefficients and Standard Errors of Female Children for Selected Quantiles

Explanatory Variables	5th Quantile β (SE)	10th Quantile β (SE)	25th Quantile β (SE)	50th Quantile β (SE)	75th Quantile β (SE)	85th Quantile β (SE)	90th Quantile β (SE)	95th Quantile β (SE)
Age (months)								
0 – 5[C]								
6 – 11	1.70(0.23)*	1.37(0.11)*	0.84(0.12)*	0.53(0.08)*	0.29(0.09)*	0.26(0.11)*	0.21(0.13)	-0.14(0.16)
12 – 23	1.68(0.20)*	1.26(0.10)*	0.67(0.10)*	0.25(0.07)*	-0.12(0.09)	-0.26(0.09)*	-0.32(0.11)*	-0.43(0.16)*
24 – 35	1.99(0.21)*	1.58(0.10)*	0.92(0.10)*	0.52(0.07)*	0.18(0.08)*	0.02(0.09)	-0.14(0.11)	-0.34(0.16)*
36 – 47	1.93(0.20)*	1.48(0.10)*	0.76(0.10)*	0.38(0.07)*	-0.00(0.08)*	-0.15(0.09)	-0.19(0.12)	-0.47(0.14)*
48 – 59	1.65(0.20)*	1.19(0.10)*	0.43(0.10)*	-0.05(0.07)	-0.51(0.08)*	-0.69(0.09)*	-0.75(0.12)*	-0.99(0.14)*
Location of Residence								
Rural[C]								
Urban	-0.11(0.08)	-0.08(0.05)	-0.09(0.05)	-0.07(0.05)	-0.01(0.06)	-0.01(0.06)	-0.05(0.08)	-0.16(0.11)
Mother's Level of Education								
No formal education[C]								
Primary education	-0.04(0.07)	-0.01(0.07)	0.03(0.06)	0.03(0.06)	0.17(0.05)*	0.15(0.07)*	0.13(0.10)	0.18(0.13)
Secondary education	-0.08(0.09)	0.01(0.06)	0.11(0.06)	0.08(0.05)	0.15(0.05)*	0.21(0.06)*	0.18(0.09)	0.17(0.11)
Tertiary education	-0.01(0.10)	0.02(0.09)	0.12(0.08)	0.17(0.08)*	0.23(0.09)*	0.33(0.09)*	0.32(0.14)*	0.36(0.20)
Geopolitical Region								
South East[C]								
South South	0.03(0.12)	0.03(0.09)	0.01(0.07)	0.05(0.06)	0.07(0.08)	0.14(0.09)	0.03(0.14)	-0.01(0.15)
South West	0.05(0.15)	-0.10(0.08)	-0.08(0.07)	-0.01(0.07)	-0.11(0.07)	-0.09(0.10)	-0.13(0.14)	-0.20(0.16)
North Central	0.26(0.12)*	0.22(0.08)*	0.19(0.06)*	0.24(0.06)*	0.30(0.07)*	0.37(0.09)*	0.33(0.12)*	0.28(0.14)*
North East	-0.08(0.14)	-0.05(0.09)	-0.02(0.07)	-0.01(0.06)	0.07(0.08)	0.16(0.10)	0.13(0.13)	0.14(0.17)
North West	-0.08(0.12)	-0.11(0.08)	-0.08(0.07)	0.06(0.07)	0.11(0.07)	0.23(0.09)*	0.18(0.13)	0.17(0.15)

* $p<0.05$ C = Reference Group SE = Bootstrapped Standard Error of 200 Resamples

Table 4.6 (Cont'd): Quantile Regression Coefficients and Standard Errors of Female Children for Selected Quantiles

Explanatory Variables	5th Quantile β (SE)	10th Quantile β (SE)	25th Quantile β (SE)	50th Quantile β (SE)	75th Quantile β (SE)	85th Quantile β (SE)	90th Quantile β (SE)	95th Quantile β (SE)
Parent's Wealth Status								
Poorest^C								
Poorer	0.11(0.09)	0.11(0.07)	0.11(0.05)*	0.18(0.05)*	0.15(0.06)*	0.16(0.07)*	0.14(0.08)	0.07(0.12)
Middle	0.23(0.09)*	0.15(0.06)*	0.03(0.06)	0.12(0.06)*	0.11(0.06)	0.05(0.08)	0.11(0.10)	0.14(0.13)
Richer	0.19(0.12)	0.06(0.08)	-0.12(0.07)	-0.08(0.06)	-0.10(0.08)	-0.12(0.09)	-0.07(0.10)	-0.15(0.15)
Richest	0.15(0.14)	0.04(0.09)	-0.13(0.08)	-0.12(0.08)	-0.18(0.09)*	-0.21(0.10)*	-0.20(0.12)	0.00(0.20)
Household Size								
1 – 4^C								
5 – 8	-0.04(0.08)	0.01(0.06)	0.00(0.05)	0.00(0.05)	-0.02(0.05)	-0.02(0.07)	0.08(0.07)	0.04(0.11)
> 8	-0.02(0.06)	-0.03(0.05)	-0.04(0.04)	-0.03(0.04)	-0.03(0.04)	-0.04(0.06)	-0.01(0.07)	-0.08(0.09)
Constant	11.18(0.25)*	12.12(0.12)*	13.59(0.13)*	14.74(0.09)*	15.99(0.11)*	16.60(0.14)*	17.09(0.17)*	18.12(0.24)*
5th Quantile Pseudo R^2	0.06							
10th Quantile Pseudo R^2	0.04							
25th Quantile Pseudo R^2	0.02							
50th Quantile Pseudo R^2	0.02							
75th Quantile Pseudo R^2	0.02							
85th Quantile Pseudo R^2	0.02							
90th Quantile Pseudo R^2	0.02							
95th Quantile Pseudo R^2	0.02							

* $p<0.05$ C = Reference Group SE = Bootstrapped Standard Error of 200 Resamples

4.8 GOODNESS OF FIT / MODEL SUMMARY

Table 6 – 8 show the coefficient estimates and 200 resamples bootstrapped standard error for each selected quantile, the tables also contains Pseudo R^2 for each selected quantile at 5% level of significance.

For the total, male and female participants, it was observed that the Pseudo R^2 decreased with increasing quantile. Considering the total participants, at the 5th quantile a Pseudo R^2 of 0.06 implies that 6% of the variation observed in BMI can be explained by Age (months), sex, location of residence, mother' level of education, geopolitical region, parent's wealth status and household size. A Pseudo R^2 of 0.04 at the 10th quantile means that 4% of the variation in BMI of the total sample under-five children can be explained by the regression line of the 10th quantile, whereas, a Pseudo R^2 of 0.02 at the 95th quantile means that 2% of the variation in total sample children BMI can be explained on the basis of the regression line of the 95th quantile.

CHAPTER FIVE

5.0 DISCUSSION, CONCLUSION AND RECOMMENDATIONS

5.1 DISCUSSION

This present study was conducted to investigate the factors associated with the nutritional status of under-five children in Nigeria, using their BMI.

The inherent characteristics of the children's BMI was characterized by a significant test of normality, revealing the great importance of the quantile regression model in its ability to accommodate the robustness the children's BMI (Beyerlein *et al,* 2008). This finding is consistent with BMI distribution of infants and children in South Africa which shifted to the right (Ramokolo *et al*, 2015). This is also in agreement with the positively skewed BMI distribution of Chinese adults (Ouyang *et al*, 2015).

A finding of the study shows a significant association between age and BMI. This is in agreement with several studies on children nutritional status (Takele, Zewotir and Ndanguza, 2019; Amadi, Ezenwosu and Odetunde, 2018). The lower quantiles were positively associated with BMI, whereas, the upper quantiles were negatively associated with BMI. This means that children aged 0 – 5 months compared to other ages are less likely to have increase BMI in the lower quantiles but more likely to have increase BMI at the upper quantiles. This effect showed in the lower quantiles can be attributed to the effects of breastfeeding, which is a child's exclusive food for the first six months of life (WHO, 2001). Effective and exclusive breastfeeding have been found to help mitigate against childhood malnutrition (Scott, Ng and Cobiac, 2012; Yan *et al,* 2014).

The results also revealed that sex was related with BMI across all the selected quantiles. This means that male children were more likely to increase in BMI than their female counterpart. This agrees with a study carried-out among children, though aged 7 – 12 years in Kuala

Lumpur, Malaysia (Khor *et al,* 2011). Profound factors to this effect have been African cultural norms and age-long practice of societal negligence of female children (Amadi, Ezenwosu and Odetunde, 2018; Ahmad, Khalil and Khan, 2011).

The result of this study showed that location of residence was not associated with BMI for all the participants and the female children at any of the selected quantiles, but was negatively associated at the 85th quantile for the male children. This is consistent with the findings of a longitudinal study conducted among Canadian children, that dwelling in urban area is negatively associated with BMI (Oliver and Hayes, 2008).

The findings of this study showed that mother's level of education was associated with an increase in BMI across the quantiles. The higher the mother's level of education the more likely the children are to increase in BMI. This is in coherence with a study that reported that children whose parents have high school or university education are more likely to be overweight and obese (Karki, Shrestha and Subedi, 2019). It indicated that children of educated mothers are more likely to have increase BMI. This can be attributed to their better child care, healthy eating and feeding practices which resultantly affects children's nutritional status (Alderman, Hentschel and Sabates, 2003).

The result shows that for North East and North West, there is a negative significant association with BMI at the 10th quantile for all the participants and the male children, whereas, the magnitude of the changes for North Central changes across the BMI distribution with a positive significant association at all the selected quantiles for the female participants. This means that children from North East and North West are less likely to increase in BMI than children from South East. This corresponds with the report of USAID 2018, which reported that children from the North East and the North West are the most malnourished in Nigeria. Insecurity menace leading to displacement of families, low level of education, poor government intervention are likely associated factors.

The findings of the study show that parent's wealth status was found to be significantly associated with BMI. The children from the poorer and middle wealth status were more likely to increase in BMI than children from the poorest wealth status. At the 25th quantile, for both children from the richer and the richest wealth status, they were less likely to increase in BMI compared to their counterparts from the poorest wealth status. This is contrary to the findings of Galgamuwa *et al,* 2017, which found that low socioeconomic status was significantly associated with malnutrition in children. This was elucidated by Acquah *et al* 2019, that wealth is not in direct relationship with food intake and availability of food does not guarantee balanced diet, but high purchasing power to afford quality and healthy food for their family depends on access to sufficient resources.

Result of this study shows that household size was not a significant factor associated with BMI. This is contrary to the findings of the study in Mbeere South District in Kenya, which reported a significant effect of household size on children's nutritional status (Badake *et al,* 2014). Also, children from large household size have been found to be malnourished (Aiga *et al,* 2019; Wolde, Berhan and Chala, 2015; Wong, Moy and Nair, 2014).

5.2 STRENGTHS AND LIMITATIONS OF THE STUDY

One of the major strengths of this study is the use of a nationally representative sample which gave a better reflection of the nutritional status of under-five children in the country. The determination of the inherent distributional nature of the outcome variable also helped to facilitate the use of a better statistical modelling methodology. Furthermore, the quantile regression model permits full exploration of the explanatory variables across the distribution of the dependent variable.

In contrast to the strengths of this study, the effect of mother's characteristics such as age and BMI, and child dietary intake was not assessed on the children's BMI as these were not provided by the used dataset.

5.3 CONCLUSION

Generally, the result of the children's BMI a measure of their nutritional status was relatively low, this signifies that the nutritional status of under-five children is still a problem of public health importance in Nigeria.

The effects of an increase in mother's level of education was associated with a positive increment in children's BMI. Likewise, male children were more likely to increase in BMI compared to their female counterpart. It was revealed that the effect of location of residence and household size of both sexes was not associated with the children's BMI.

This study exhibited the importance of the test of normality on outcome variable in determining what type of model to use, shows relevant importance of quantile regression model in modelling non-normal outcome variable and conclusively that an urgent national public health problem of under-five children nutritional status needs proactive measures.

5.4 RECOMMENDATIONS

The findings from this study gives the following recommendations:

It is pertinent to always determine and validate the distribution of an outcome variable as this guides better conclusion and implementation.

For non-normally distributed continuous outcome variable, the quantile regression model is recommended for model fitting and estimation.

Furthermore, policies to improve the nutritional status of under-five children should be improved and continuously monitored.

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