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TOPIC

ANALYSIS OF REPEATED MEASURES OF WEIGHT OF CHILDREN UNDER FIVE YEARS, A COMPERATIVE ANALYSIS BETWEEN MALE AND FEMALE CHILDREN

(CASE STUDY: TAMALE METROPOLIS)

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(Bsc Statistics)

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(CASE STUDY: TAMALE METROPOLIS)

BY

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DECLARATION

This thesis is submitted to KNUST, School of Graduate Studies through the College of Physical Science. I hereby declare that this thesis is my independent work and has not been accepted in any previous application for a degree here or elsewhere. This thesis presents results of original research undertaken by the undersigned. Information taken from other works has been specially and duly acknowledged.

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DEDICATION

This work is dedicated to my wife, my daughter and the entire family for the enormous support love and encouragement they gave me in the course of writing the thesis.

ABSTRACT

Repeated measures data has grown increasingly within the past years because of its ability to monitor changes both in within and between subjects. Statisticians in many field of study have chosen method of collecting data because it is cost effective and also minimizes the number of subjects required to produce a meaningful outcome. This thesis seeks to describe the use of several methods to analyze repeated measure using data collected on weight of children under five years of age at the weighing centers in Tamale metropolis in the northern region. The question of interest is to find out if there is a change in mean weight gain by children under five year over time and if the factors (age, feeding type, feeding practice gender etc) influence those changes. The data was collected from 210 children put into three groups of ages 0-6 months, 7-12 months and 13-18 months on monthly bases for a total of 1260 observations. Three feeding types: exclusive breast feeding, breast feeding with introduction of plumpy nut food supplement and completely complementary feeding. Univariate ANOVA and multivariate MANOVA techniques were use to analyzed the data. Both random effect and fixed effect models shown to be better for the data.

Age, feeding type and feeding practices were the factors that did not support the null hypothesis and therefore influencing the children weight gain with the p-values of <0.001 at 5% level in all the three cases. Gender of the children is not an influencing factor of weight gain by children. Other factors such as mother's occupation, birth position of the children to their mothers and birth position were all tested negative to weight gain by the children.

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ABBREVIATIONS AND ACRONYMS

ANOVA	Analysis of Variance
WHO	World Health Organization
MANOVA	Multivariate Analysis of Variance
NCHS	National Center for Health Statistics
UNICEF	United Nations Children's Fund
CDCP	Center for Diseases Control and Prevention
MOH	Ministry of Health
IMMPaCt	International Micronutrient Malnutrition Prevention Program
CDC	Center for Diseases Control
USAID	U. S. Agency of International Development
GAIN	Global Alliance for Improved Nutrition
FFI	Flour Fortification Initiative
VPDs	Vaccine Preventable Diseases
CMAM	Community Base Management of Acute Malnutrition
TTH	Tamale Teaching Hospital
MHD	Metropolitan Health Directory
NRC	National Rehabilitation Center
NCHS	National Center for Health Statistics
CSPD	Child Survival, Protection and Development
IVP	Irrigation Village Perimeters

CHAPTER ONE

INTRODUCTION

1.1Introduction

Repeated measures data are encountered in a wide variety of disciplines, including business, behavioral science, agriculture, ecology, and geology. What distinguishes repeated measures data from time series data is that multiple subjects are involved in the former, and the number of measurements per subject is generally not very large.

When several measurements are taken on the same experimental unit (e.g. involving persons, animals, or machines), the measurements tend to be correlated with each other. When the measurements represent qualitatively different things, such as weights, lengths, and widths, the correlation is best taken into account by the use of multivariate methods, such as Multivariate Analysis of Variance (MANOVA).

MANOVAis a technique that measures the differences of two or more metric dependent variables based on a set of categorical (nonmetric) variables acting as independent variables. When the measurements represent responses to treatments or levels of the experimental factor of interest, such as time, the correlation can best be accounted for by performing a repeated measures analysis of variance. An experimental design that accommodates this type of measurement is the repeated measures design. A repeated measures design refers to studies in which the same measures are collected a multiple of times for each subject, but under different conditions.

A popular repeated-measures design is a crossover study defined as a longitudinal study in which subjects receive a sequence of different treatments (or exposures). Many important crossover studies are controlled experiments, even though they are observational studies in nature. Repeated measures design has many advantages.

The first advantage is that of reducing the variances of estimates of treatment-effects and thereby, allowing statistical inferences to be made with fewer subjects. The design also has primary strength of making an experiment more efficient and helps keep the variability low. This helps to keep the validity of the result higher while still allowing for smaller than usual subjects groups. Also, it helps facilitate in studying the changes in participant's behavior over time.

The design however, suffers the disadvantage that it may not be possible for each participant to be in all conditions of the experiment simultaneously (i.e. time constraints, location of experiment, e.t.c.). Also, there are several threats to the internal validity of this design, namely a regression threat (when subjects are tested several times, their scores tend to regress toward the mean), a maturation threat (subjects may change during the course of the experiment) and a history threat (events outside the experiment that may change the response of subject between the repeated measures) (Vonesh et al, 1997).

1.2 Background of the study

Proper nutrition of children leading to weight gain as a measure of growth and good health is the essential foundation of human development. Despite global efforts for improving maternal and child health, and specific efforts like Integrated Child Development Service (ICDS), malnutrition among children remains a significant problem in many parts of the world. In India for instance, the proportion of underweight, stunting and wasting among under-three year old children have been reported to be 47%, 45%, and 16% respectively at the national level (NHFS-2, 1998).

Infant feeding practices constitute a major component of child caring practices apart from socio-cultural, economic and demographic factors. Somehow, these practices happen to be one of the most neglected determinants of weight of children at their early stages of growth. Recent studies have recognized the link between malnutrition and child feeding practice (Kapur D. etal, 2005).

Children gain weight and grow more rapidly during infancy and childhood than at any other time in life. However, some children fail to gain weight at a normal rate, either because of expected variations related to genes, being born prematurely, or because of undernutrition, which may occur for a variety of reasons. Undernutrition is sometimes called a growth deficit or failure to thrive.

It is important to recognize and treat children who are not gaining weight normally, because it may be a sign of undernutrition or an underlying medical problem that requires treatment. This, according to UNICEF (2006), is because, each year, undernutrition contributes to the deaths of about 5.6 million children younger than 5 years, in the developing world. Another 146 million children within this age group are underweight and are at an increased risk of early deaths, illness, disability and underachievement (UNICEF, 2006). The organization also reported that in least developed countries, 42 percent of children are stunted and 36 percent are underweight. Apart from deaths in children, undernutrition can have complications, such as a weakened immune system, shorter than normal height, or difficulties with learning. These complications are more common in children who are undernourished for a long period of time.

Poor weight gain is defined as gaining weight at a slower rate than other children who are the same age and sex. "Normal" ranges for weight and height are based upon the weight and height of thousands of children. In the United States, standard growth charts are published by the

Centers for Disease Control and Prevention; these charts are available for boys and girls and are appropriate for all races and nationalities. Weight gain normally follows a predictable course from infancy through adolescence. However, some children do not gain weight normally from birth, while other children gain weight normally for a while, then slow or stop gaining weight. Weight gain usually slows before the child slows or stops growing in length. A child is said to have poor weight gain if he or she does not grow at the expected rate for their age and sex. Poor weight gain is not a disease, but rather a symptom, which has many possible causes. Three factors account for poor weight gain in children.

The first factor includes not consuming adequate amount of calories or the right combination of protein, fat, and carbohydrates. The second factor is when the child is not absorbing adequate amount of nutrients, which leads to poor weight gain. The third factor has to do with requiring a higher than normal amount of calories.

Poor weight gain can occur as a result of a medical problem, a developmental or behavioral problem, and lack of adequate food, a social problem at home, or most frequently, a combination of these problems.

If an infant or a child slows or stops gaining weight, it is important to try to determine and treat the underlying cause. The first step is a complete medical history and physical examination. Most children will not require blood testing or imaging tests, although testing may be recommended in certain situations. Parents should also mention if they have eliminated foods from the child's diet due to concern about the effects of these foods (e.g. abdominal pain, diarrhea, "hyperactivity").

The provider may also ask about the child's household, including who lives in the child's house, if there have been recent changes or stresses (e.g. divorce, illness, death, new sibling), or if anyone in the house has a medical or psychiatric illness. The provider may also ask about the food supply (e.g. if there have been days when anyone in the family went hungry because there was not enough money for food). Although these questions can be difficult to answer, it is important to be honest.

1.2.1Growth Monitoring In Infants and Children

For a relatively small expenditure per child, growth monitoring can greatly strengthen preventive health programmes. Growth is the best general index of the health of an individual child, and regular measurements of growth permit the early detection of malnutrition, frequently association with diarrhea, and other illnesses, when remedial action is relatively easy. Although acute signs of malnutrition are easily noted by health workers, it is often too late, and always more expensive, to help the severely malnourished children.

For early detection of children with growth retardation and high risk of malnutrition and mortality, health workers need special tools and training in growth monitoring. The growth status of children is a measure of the health and well-being of the whole community. Birth weight is of a particular significance in determining the nutritional status of a community, as low birth weight is a good indicator of subsequent illness and death in children.

Various body measurements are used to access growth. Some are easier to use, more accurate and more useful than others. Monitoring the growth of a child usually requires taking the same measurements at regular intervals and seeing how they change. A single measurement only indicates the child’s size or weight is increasing, staying the same, or declining. Careful repeated measurements and comparisons with previous measurements are necessary because most children will continue to grow a little, unless they are very ill, and it is easy to mistake some growth for adequate growth. Growth measures are usually compared to a reference population. Gathering data to establish a local reference population is a major undertaking. Therefore, western standards are usually used for comparison, such as Tanner and Boston, or more recently, those of the National Centre for Health Statistics (NCHS).

1.2.2 Weight-For-Age of Children

To obtain weight-for-age, the weight of the child (in kgs) is compared with that of an ideally healthy child of the same age from a reference population. This is the basis of the weight-for-age, or Gomez classification of nutritional status. A child weighing less than 60 per cent of the reference weight-for-age is considered to be severely malnourished. For these reasons, countries have different ways of assessing the growth of children through weight taking and at different places. For instant, in Indonesia 2.5 million infants and young children are being weighed regularly at the traditional monthly meetings of village women. The results are entered on growth charts kept by the mothers themselves.

In Thailand, a programme based on the home use of growth charts by parents in several villages, helped to eliminate completely third degree malnutrition, and reduced second degree malnutrition by 44 per cent during 1981 – 1982, even though no additional food was provided.

In Colombia, improvements in weight gain for a majority of children suffering from mild, moderate and severe malnutrition have been achieved in poor communities by nutrition programmes incorporating the "Carnet de Salud" or health card kept at home by mothers. In

Jamaica, a systematic programme to improve the health and growth of over 6,000 young children using growth charts, immunization and nutrition education and milk supplements, has resulted in a 40% decline in the prevalence of malnutrition and a 60 percent fall in infant mortality (UNICEF, 1985).

In Ghana, many cultures have traditionally used a variety of indicators to measure their children's growth and development. These were taken into consideration and used by the community health workers to understand the community's perceptions, so that they could be related to the use of growth charts. In Ghana, especially in the rural communities, mothers believe that their children are growing well when they: have a good appetite; are fat rather than thin; learn new things at the right time; seem heavier when lifted; have normal bodily functions, healthy skin and general appearance; have a good humour, are happy and active; and sometimes when they are growing taller. Bead strings tied around the waist, legs or wrists of children are also used as indicators to measure growth. By the time a child is five months old, the bead strings around the waist should have been changed or adjusted five times.

1.2.3 Interventions to Improve Weight Gain of Infants and Children

In 2000, the Center for Diseases Control and prevention (CDCP) established the International Micronutrient Malnutrition Prevention and Control Program (IMMPaCt) to support the global effort to eliminate vitamin and mineral deficiencies, or hidden hunger in both developed and developing nations. Through the IMMPaCt program, CDC provides funding and/or technical assistance directly to countries through cooperative and interagency agreements with UNICEF, the World Health Organization (WHO), the U.S. Agency of International Development (USAID), and the Global Alliance for Improved Nutrition (GAIN), and the Micronutrient

Initiative (MI). With these partners, CDC has assisted countries in assessing the burden of hidden hunger through national surveys and surveillance systems that allow countries to monitor the coverage and impact of their food fortification and micronutrient supplementation programs. In addition, computer and web-based training tools and regional and national training workshops developed by CDC have strengthened the capacity of countries to assess the burden of poor weight gain through malnutrition, track the effectiveness of interventions strategies through surveillance systems, and plan social marketing and health communication strategies to promote the consumption of vitamin- and mineral-fortified foods.

In 2002, in collaboration with the WHO Eastern Mediterranean Regional Office (EMRO), CDC provided funding support and consultation toward a national micronutrient survey to generate baseline data on iron status of adult women and preschool children in order to monitor the impact of the recently initiated national flour fortification program in Jordan.

To help improve nutrition worldwide, the CDC IMMPaCt Program helped launch the Flour Fortification Initiative (FFI) in 2002. The Initiative was formalized in 2005. The FFI Leaders Group, a network of government and international agencies, wheat and flour industries, academia, and consumer and civic organizations, was established to promote flour fortification. FFI supports fortification of flour with essential vitamins and minerals, especially folic acid and iron, as one important way to help improve the nutritional status of populations, especially women and children, around the world.

In many Asian and African countries commercially produced infant foods are either not commonly used or readily accessible through markets in remote areas. Through the IMMPaCt program, CDC is actively planning pilot interventions in Kenya and Tajikistan to assess the feasibility of alternative approaches to sustainable distribution, through small local markets and house-to-house sales, of easy-to-use, “in-home” fortificants to enrich baby foods. These efforts will require public-private-civic sector partnerships to be nurtured and strengthened over time.

1.2.4 Infectious Disease Interventions that Improve Infant and Child Weight Gain

Over recent decades, the experience of national immunization programs demonstrates that immunization is one of the “best buys” in public health. Rapid implementation and use of the traditional vaccines against childhood killer diseases has been the single most important contributor to the reduction of child mortality in developing countries.

Prevention of vaccine preventable diseases (VPDs) has the potential to positively impact malnutrition. Pertussis infection (whooping cough) is associated with coughing followed by vomiting that can last several months. This has been shown to result in poor growth and lower than normal weight for age, along with the potential to result in malnutrition.

Several studies suggest that children vaccinated against measles may have improved nutritional status compared with unvaccinated children. Fewer deaths due to diarrhea and malnutrition have also been reported in children vaccinated against measles. Infections, including those preventable by immunization, have been shown to lower the body’s immune defenses leading to more infections, lowered nutritional intake and eventual malnutrition. For example, measles infections are associated with lowered levels of Vitamin A, which increases susceptibility to diarrhea and pneumonia. These infections result in poor appetite, lowered food intake, and the potential for malnutrition. Studies from one African country demonstrated a decrease in the number of malnutrition cases that was temporally related to a mass measles vaccination campaign that improved control of measles.

In collaboration with WHO, UNICEF and other agencies, CDC's Global Immunization Division has been involved in international activities to improve immunization coverage rates for all vaccine preventable diseases. Global routine measles coverage increased from 71 percent in 1999 to 76 percent in 2004. Overall, global measles-related deaths decreased 48 percent from 1999 to 2004, i.e., from 871,000 people to 454,000. CDC is also a founding member of the Measles Partnership, which from 2001 to 2005 supported 40 African countries in conducting mass measles vaccination campaigns. An estimated 213 million African children were vaccinated, averting 1.2 million measles-related deaths. The Partnership is also supporting measles vaccination in WHO's Eastern Mediterranean and South East Asia Region, where 60 million children are to be vaccinated in 2006. These activities have the potential to impact on malnutrition by greatly reducing the risk of developing measles infection (UNICEF, 2006).

1.3 The Study Area

Tamale metropolitan assembly is one of the 20 administrative districts in the Northern Region of Ghana with Tamale as its capital. It has a land area of 750 square kilometers, constituting about 13% of the entire northern region. It is located at the central part of the Northern Region providing an inland port for the country to serve the other two northern regions, namely Upper West and East Regions, and also to the neighboring landlocked countries like Burkina Faso, Mali, and Niger. Tamale metropolis has a total population of about 293,881 with 146,979 male and 146,902 females (population and housing census, 2000). It has an average population density of 318.6 persons per square kilometer which is about 12 times higher than the regional average population density of 25.9 persons per square kilometer. The study is targeted on infants and children less than 5 years in the area. Parents, spatially mothers, as well as care takers will also be considered. The metropolis is predominated by Dagombas and Gonjas. However, there are quite a number of ethnic groups such as Mampurisi, Akans, Ewes, Frafra etc.

Economically, farming is the most engaged activities of the people, even though it is of the small-scale farming type. Studies indicate that about fifty-two (52%) of the indigenous people in the area are farmers (Statistical Service Department).

Tamale metropolis has a teaching hospital, the Tamale Teaching Hospital (TTH), and three other hospitals namely; the Central hospital, West hospital and Kpalsi South Polyclinic. Apart from these known hospitals, it has about seven other private clinics spread across the city especially in the rural outskirts. Weights of children are recorded in all the hospitals on monthly bases from age 0 to 60 months of age. The study seeks to analyze the repeated measurements of these weights of children in the metropolis.

1.4 Statement of the Problem

Weight gain at the infant stage of children is an important indication of growth in their early years of life in every society. Children gain weight and grow more rapidly during infancy and childhood than at any other time in life. Regular assessment of weight gain and growth pattern among children are the major preventive tools to detecting the underweight and overweight in the society.

In Ghana, weights monitoring of children stats immediately after birth and are continually done on monthly bases at every public and private maternity center. Since the growth and health of a child is paramount to the objectives of every nation, Ghana instituted compulsory immunizations against the six childhood killer diseases for children at different stages during the early stages. Diseases such as Tuberculosis, Poliomyelitis, Diphtheria, Pertussis etc. are seriously taken care of in order to maintain healthy growth among children. Tamale metropolitan health directory (MHD) has instituted policies to increase coverage and intensity of growth monitoring and promotion. It has over nine (9) established weighing centers where nursing mothers attend with their children every month for their weight to be taken. Weight change among individual children could be attributed to so many factors, including socio-economic status of parents, mothers marital status or biologically as variation related to genes or premature births. Researches reveal that, children who show poor weight could be a sign of malnutrition while those who gain weight rapidly during infancy could be at an increased risk of childhood obesity.

The weight records at the centers in the metropolis have since been available and attempt to model it to communicate to individual is lucking. Parent do not see the need to continue the monthly visit to the weighing centers as important and for that matter often feel relax in attending. It is therefore significant to examine factors associated with weight gain, and specifically the relationship between infant feeding practice and weight gain as it is one of the few potentially modifiable risk of malnutrition or childhood obesity.

It is in line with this the study takes a regular and critically analysis of the monthly repeated measurements of children's weights taken at the weighing centers in the metropolis. The study therefore seeks to adders the issue of finding an effective and reliable means of preventing weight lost of children.

1.5 Objectives of the Study

1. The main objective of this study is to use mathematical models to access the change in weight gain of the children under-five years in Tamale metropolis of the northern region of Ghana.
2. Perform Analysis of Variance Test to determine if there is significant difference in weight gain between male and female children under five (5) years.
3. Determine if there is an effect of factors such as sex, socio-economic status of the parents, marital status of the mother and infant-feeding practice on weight gain of children under-five years.

1.6 Methodology

The data for the analysis of the study will be from a primary source obtained from four weighing centers selected in the Tamale metropolis, namely the Tamale Teaching Hospital, the Choggu Weighing Center, Sakasaka Community Nursing Training School and the Kpalsi South Polyclinic. The data would be collected on weights of children between zero (0) to sixty (60) months old children in six (6) months period indicating their sex, marital status of mothers, mothers age, infants feeding practice used by mothers, socio-economic background of parents and the educational level of the mother.

Senior nurses at the selected weighing centers would also be contacted for some literature on causes of poor weight gain of infants and children both at birth and after birth. Statistics on underweight, overweight and wasting would also be collected from the metropolitan health directorate.

To achieve the objectives of the research multivariate data analysis (MANOVA) would be employed as the main statistical tool for analyzing the data. The six months will be the subjects (levels or treatments) of the factor "TIME" and gender (male and female) will be the group. Interest will be on between-subject effect (such as GROUP), within-subject effect (such as TIME) and the interactions between the two types of effects (GROUP × TIME). Also regression analysis will be considered. The response variable in the case of the regression analysis will be infant weight gain of the children with other factors (sex of the child, mother education level, marital status of the mother, child feeding practice among others) as the predictor variables for the model.

Statistical packages such as SAS and GENSTAT will be used in performing the analysis in order to obtain the results and the source of reading and reference materials from KNUST library, College of Science library and the internet.

1.7 Justification of the Study

From the economic point of view, malnutrition and child obesity have been observed to be some of the factors that slow down economic growth, by reducing the capacity and efficiency of the labor force of a country. Economics theory states that "the quantity of production of a given output is a function of many factors such as; labor force, capital stock, available quality labor, e.t.c.. It can thus be argued that, infants' poor weight gain (malnutrition) or over weight (child obesity) can affect greatly the future labor force of the country, and reduce the total output of the nation.

Apart from the economic point of view, early detection of poor weight gain is crucial since it can have complications such as a weakened immune system, shorter height, abnormal and or difficulties in learning. Early detection is therefore important to sustain the needed health and growth in the country.

It is as a result of these problems that research is deemed necessary to make in-depth studies into the monthly measurement of the children weight at the infant stage to address any anomalies that may be herein.

1.8Organization of the Study

The thesis will be divided into five chapters. Chapter one focuses on the background history of weight gain of children, the rational for the study, study objectives, overview of the general study and the organization of the thesis. Chapter two presents a review of literature relevant to the study topic. This will be followed by summary of the basic concepts of repeated analysis and how these concepts are applied. Chapter three will outline the study area and the study population, an overview of the modeling technique that will be used and data source and management. Chapter four will be presenting the analysis of the outcome of the study and its discussion and chapter five will look at the summary of the key findings of the study and the required recommendations.

CHAPTER TWO

REVIEW OF RELATED LITERATURE

2.1 Introduction

Repeated-measures designs are very common in many fields of study because of their logistical and statistical efficiency. This chapter describes repeated-measures designs and the ways in which data from a repeated-measures design can be constructed.

A repeated-measures design measures each subject or unit two or more times. For example, one might record weights of children subjected to different diets at several different time points. Or, one might record the heights of a plants to which herbicides have been applied every week for six weeks. This is the basic reason why a special analysis is required to analyze these types of data. The approaches used to model repeated- measures data vary from one to another, depending on the purpose of the study and data availability. This chapter provides a review of recent studies into repeated-measures and various methodologies commonly used in the analysis of such data as well as a discussion of findings in this field of studies. The literature review focuses primarily on growth monitoring in the northern region of Ghana and the types of analyses available in these area of study.

2.2 A REVIEW OF GROWTH MONITORING IN NORTHER REGION

2.2.1Growth Monitoring

According to the Metropolitan Health Directorate (MHD, 2011), effective growth monitoring was carried out throughout the metropolitan in both static and outreach clinics during the year under review. It continues to be used as an indicator for the assessment of the nutritional status of children < 5 years by the Ghana Health Service. The coverage of growth monitoring in the metropolis has seen a tremendous increase from 2006 at 10.3% to 2011 at 79.4 %. Below are bar graphs showing the coverage and the trends of the various forms of malnutrition at Sub-District levels as well as the District level

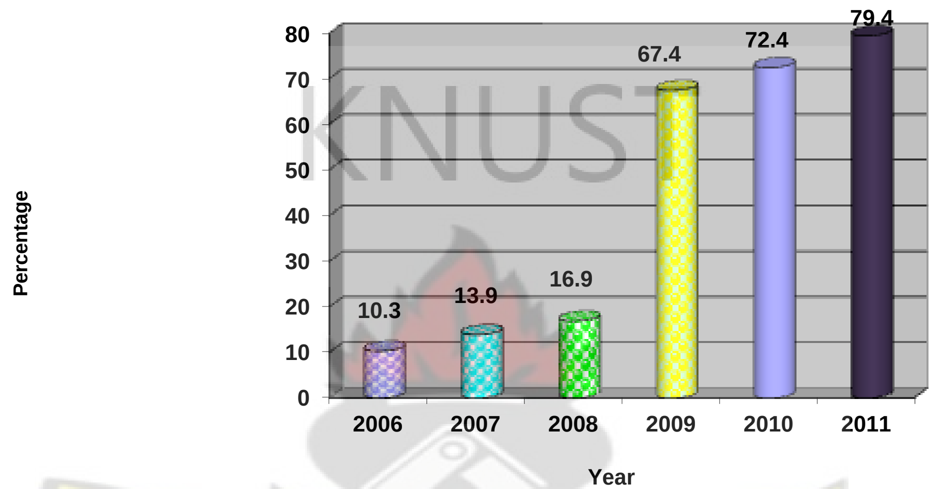
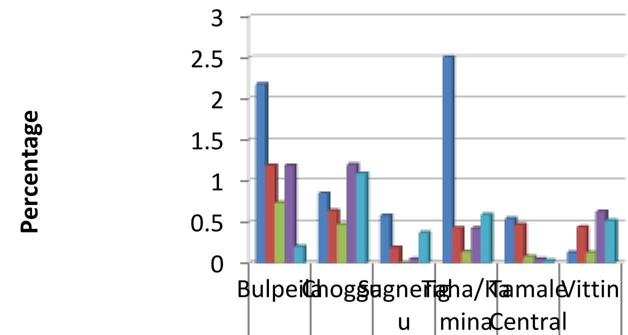


Fig 2.1 Coverage of growth monitoring of children < 5 years in the Tamale Metropolis (2006-2011)

It is shown from figure 2.1 that most of the Sub-districts recorded an increase in their coverage of monitoring over the years with the total coverage for the district recorded an increase as compared to the previous years.



	Bulpei	Chogg	Sagnerigu	Taha/Kamina	Tamale Central	Vittin
2007	2.18	0.85	0.58	2.51	0.54	0.13
2008	1.19	0.64	0.19	0.43	0.47	0.44
2009	0.74	0.47	0.00	0.14	0.08	0.13
2010	1.19	1.2	0.05	0.43	0.05	0.63
2011	0.2	1.09	0.37	0.59	0.03	0.52

Fig 2.2 Malnutrition (<60%) among children 0-59 months at Sub-district Level

From the statistics recorded at the sub-district level, Severe Malnutrition among children 0-59 months in all the sub-districts decreased as compared to last year except Taha and Sagnerigu. The report concluded that, the review will be used as an indicator for the assessment of the nutritional status of children < 5 years by the Ghana Health Service.

2.2.2 The Nutrition Rehabilitation Center

The Tamale Nutritional Rehabilitation Center (NRC) is the only functioning rehabilitation center in the Metropolis. It carries out nutritional management of severely malnourished children (<60% W/A). The center uses mainly plumpy nuts to recuperate severely malnourished children. The unit conducted a practical training for students from the Kintampo Rural Health Training school at the rehabilitation center. An in-patient training on community management of acute mal-nutrition was also included in their training.

Table 2.1Operational indicators of the NRC

Indicator	2005	2006	2007	2008	2009	2010	2011
Total admission	**80**	**35**	**36**	**57**	**25**	**125**	**137**
Successful discharge	**12**	**12**	**9**	**12**	**16**	**112**	**53**
Referral		**8**	**0**	**8**	**25**	**3**	**13**
Defaulters		**0**	**9**	**3**	**30**	**8**	**67**
Deaths		**1**	**4**	**2**	**0**	**2**	**4**

The center saw an increase in the total admission from 125 in 2010 to 137 in 2011. This was due to the constant Supply of plumpy nuts to the centre. However, the NRC recorded 4 deaths.

2.2.3 Community Based Management of Acute Malnutrition (CMAM)

Community based out – patient treatment of severe acute malnutrition was also inaugurated in the metropolis. This is a 'new' treatment for severely malnourished children that enlist the support of community volunteers in identifying children who needed this treatment. Because participants are already visiting homes in their communities, case-finding for Outpatient Care will not increase their workload. Outpatient Care uses a new medicine mixed into food, designed to heal children at home.

2.3 A REVIEW OF OTHER RESEARCH WORKS

2.3.1 Prevalence of Underweight Children in Africa

According to Dramane and Carolyn (2006), malnutrition of children (0-59 months) is a public health concern in Africa, particularly in the Sahelian countries. In their study to evaluate the trends of the malnutrition status of children under five, from the project monitoring /impact indicators, they determine that, nutritional status of children under-five continues to deteriorate in spite of better agro climatic conditions and agricultural production in many of these countries. Using data collected from the GFSI project, they conducted their analysis base on the following indicators such as Underweight (percent of children of a given age range with weight-for-age z score less than -2 or less than – 3 standard deviation) and Stunting (percent of children of a given age range with height-for-age z score less than -2 standard deviation).

In the first exploratory phase of the analysis, descriptive statistics ands factor analyses (Principal Component Analysis - PCA, Multiple Correspondences Analysis - MCA) were used. The PCA was used for the analysis of underweight children data and for the analysis of the stunted children under-five data, the use of the MCA was chosen.

The analysis of anthropometric data on the prevalence of underweight children (under five) over the period from December 2000 to September 2005 shows that this form of malnutrition continues to be a challenge (with rates > 20%) in the study zone. It reaches its peak in June with an average rate varying from 43% to 44% of weighed children. The rate of severely malnourished children (Weight/Age < -3 SD) follows the same trends as that of the rate of global malnutrition. It is largely influenced by the food availability/access at the household level (see graph 1). The minimum rate of severe malnutrition is observed in September. The maximum recorded rate is 11% in June 2005. That means that in June 2005, 11 children out of 100 in the project zone should have been referred to hospitals as emergency cases due to severe malnutrition problems.

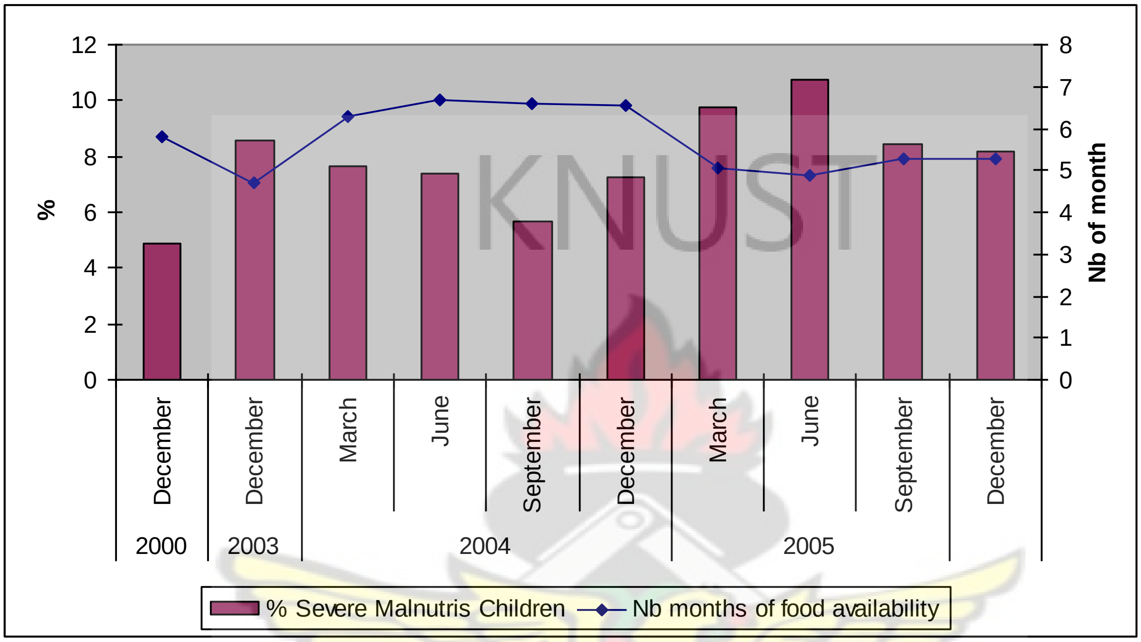


Figure 2.2: Evolution Child Malnutrition and Food Availability

The rate of underweight children under-five is more important among the sedentary population than the pastoralists. The average rate of global (severe + moderate) underweight children under-five in the pastoral zone is 37.5% (CV=38%) against 36%, 40 %(CV=26%) and 41% (CV=37%) for the children under-five in the zones of river, Irrigated Village Perimeters (IVP), and of the Lakes respectively. However the average rate of severely underweight children is higher among the children of pastoralists (8.84%) than those of sedentary IVP cereal producers (7.60%), and flooded rice growers (6.50%). The rate of severely underweight children in the livestock zone remains lower than the rate of malnourished children living in the villages located around the lakes (9.91%).

Fawzi et al (1998) studied the relationship between prolonged breastfeeding and child growth by examining prospectively among 28,753 Sudanese children less than 36 months of age enrolled in a broader cohort study of child health and nutrition. 81% of children were breast-fed at 12 months, but this prevalence declined to 62% at 18 months and 27% at 24 months. At baseline and at each of three 6-monthly follow-up visits breastfeeding status was assessed and all subjects were weighed and measured. Their results show that undernourished children were more likely to be breastfed for a longer period of time compared with normal children. They found a small difference between breastfed and fully weaned children in the gain in height over the following 6-month period. However, breastfed children were likely to gain significantly less weight, particularly among children who were aged 6-12 months. Similar findings were noted when these associations were examined among children who were normally nourished at the time of breastfeeding assessment. The inverse association between breastfeeding status and weight gain was significantly larger among children of poor or illiterate mothers compared with children of relatively more affluent or literate mothers, respectively.

In conclusion, their findings suggest that the inverse association is not causal, and may be explained by poorer complementary feeding among breastfed compared with weaned children. Children from poorer households and whose parents are illiterate are more likely to have less than adequate complementary feeding. The importance of adequate complementary feeding in the second half of infancy needs to be stressed in nutrition education programmes.

Tharakan and suchindran (1999) attempted to develop an ordinal logistic regression (OLR) model to identify the determinants of child malnutrition instead of developing traditional binary logistic regression (BLR) model using the data of Bangladesh Demographic and Health Survey

2004. Based on weight-for-age anthropometric index (Z-score), they categorized child nutrition status is into three groups. That is severely undernourished (< -3.0), moderately undernourished (-3.0 to -2.01) and nourished (≥-2.0). Since nutrition status is ordinal, an OLR model that is proportional odds model (POM) can be developed instead of two separate BLR models to find predictors of both malnutrition and severe malnutrition if the proportional odds assumption is satisfied. The assumption is satisfied with low p-value (0.144) due to violation of the assumption for one co-variate. So partial proportional odds model (PPOM) and two BLR models have also been developed to check the applicability of the OLR model. Graphical test has also been adopted for checking the proportional odds assumption. The results of their study was that all the models determine that age of child, birth interval, mothers' education, maternal nutrition, household wealth status, child feeding index, and incidence of fever, ARI &diarrhoea were the significant predictors of child malnutrition. However, results of PPOM were more precise than those of other models. They concluded justifying clearly that OLR models (POM and PPOM) are appropriate to finding predictors of malnutrition instead of BLR models.

Taina et al (2011) investigated the effect of intensified lifestyle counseling targeting infants' mothers on offspring weight development during the first 4 years of life. They use follow-up of a cluster-randomized controlled trial in primary care child health clinics during 2004–2006 in Finland. Participants received a follow-up survey during 2010 concerning weight and height measurements of their offspring. Number of clusters was six and the response rate to the follow-up was 71.9% (N=64/89). The participants (N=89) were mothers of infants aged 2–10 months. They conducted an intervention programmes such as individual counseling on diet and physical activity when the infant was 2–10 months of age and an option to attend supervised group exercise sessions. The group analyzed the secondary outcome of the intervention study: the weight development of the offspring and the primary outcome was the proportion of women returning to their pre-pregnancy weight by 10 months post partum.

The study realized that, Multilevel mixed effect non-linear regression models included group, age of the child and interaction between group and age of the child. The increase of BMI z-score between 24 and 48 months was slower among the intervention group offspring (−0.034 to −0.002, p=0.028) as compared with control group. Z-scores for weight-for-length/height did not differ between groups when the period 0–48 months was analyzed (p=0.23) but for the period of 24–48 months, between-group differences were significant (p=0.012). After the analysis of data in the study, they concluded that lifestyle counseling targeting mothers during the child's first year may be effective in slowing offspring weight gain until 4 years of age. However, larger studies are needed to confirm the findings which may have the potential in combating the obesity epidemic.

Peter et al (1902) in researching into a comparative analysis of nutritional parameters as predictors of outcome in male and female -stage renal disease (ESRD) patients reveals that many patients with ESRD are malnourished and cross-sectional studies show that markers of malnutrition may predict death. Serum albumin (S-albumin), the commonest nutritional marker, has been criticized because it is so closely related to the effects of inflammation and other non-nutritional factors. Consequently, we need other nutritional markers that can predict outcome. However, males and females differ as regards body composition and it is not known how this may influence the predictive power of different nutritional markers.

The researchers used 206 ESRD patients (126 males) aged 52±1 years, we evaluated the relationship between survival and five estimates of nutritional status (S-albumin, subjective global assessment (SGA), lean body mass (LBM), body fat mass (FM) assessed by dual-energy X-ray absorptiometry, and handgrip strength (HGS)) close to start of renal replacement therapy (RRT). The patients were also classified as regards the presence of cardiovascular disease (CVD), diabetes mellitus (DM), and inflammation (CRP≥10 mg/l). Mortality was monitored over mean follow-up period of 37±2 months. In the whole patient group, the presence of CVD, DM, inflammation, and malnutrition (SGA >1) close to start of RRT all predicted poor outcome. However, whereas inflammation strongly predicted ($P<0.0001$) poor outcome in males, no such effect was observed in females. Also, differences were found between males and females regarding the predictive value of the five different nutritional estimates. Whereas HGS, SGA, and S-albumin independently predicted poor outcome in males, only SGA predicted outcome (independently of age, CVD, and DM) in females. Mild to moderate malnutrition, as assessed by SGA, was present in 39% of the patients and predicted outcome independently of age and co-morbidity in both males and females. However, the predictive power of various other nutritional markers differed markedly between male and female patients. Whereas a low HGS was an excellent independent outcome predictor in males, no predictive power of this parameter was found in females. S-albumin is more closely related to co-morbidity and inflammation than nutritional status in patients close to start of RRT. We conclude that sex is an important factor that must be taken into account in studies on nutrition and nutritional interventions in ESRD patients.

2.4 FACTORS AFFECTING PREVALENCE OF MALNUTRITION

Salah E. et al (2006) states that, malnutrition affects physical growth, morbidity, mortality, cognitive development, reproduction, and physical work capacity, and it consequently impacts on human performance, health and survival. It is an underlying factor in many diseases for both children and adults, and is particularly prevalent in developing countries, where it affects one out of every 3 preschool-age children. A well-nourished child is one whose weight and height measurements compare very well with the standard normal distribution of heights and weights of healthy children of the same age and sex. Factors that contribute to malnutrition are many and varied. Their study was to evaluate the level of malnutrition and the impact of some socio-economic and demographic factors of households on the nutritional status of children under 3 years of age in Botswana. Factors included: the number of children under 3 years of age in the family, occupation of the parents, marital status, family income, parental education, maternal nutritional knowledge, residence location (urban or rural), gender, and breastfeeding practices. The study was a cross-sectional descriptive survey using a structured questionnaire and measurements of weight and height. Four hundred households and mothers of children under three, representing the 23 Health Regions of Botswana, participated in the study. Reference standards used were those of the National Center for Health Statistics (NCHS). EPI Info software (version 5) was used for data entry and analysis. The results show that the level of wasting, stunting, and underweight in children under three years of age was 5.5 %, 38.7 %, and 15.6 % respectively. Malnutrition was significantly ($p < 0.01$) higher among boys than among girls. Underweight was less prevalent among children whose parents worked in the agricultural sector than among children whose parents were involved in informal business. Children brought up by single parents suffered from underweight to a significantly ($p < 0.01$) higher level than children living with both parents. The prevalence of underweight decreased significantly (p<0.01) as family income increased. The higher the level of the mother's education, the lower the level of child underweight observed. Breastfeeding was found to reduce the occurrence of underweight among children. The study findings imply that efforts for redressing child undernutrition issues in Botswana should focus on factors associated with development outcomes such as maternal income, maternal education, and the creation of employment or economic engagements that do not compromise important child care practices such as breastfeeding.

Dinesh et al (2006) studied the nutritional status of under-five children and whether infant feeding practices are associated with the undernutrition in anganwari (AW) areas of urban Allahabad. Under-five-years children and their mothers in selected four anganwari areas of urban Allahabad (UP) participated in the study. Nutritional assessment by WHO criterion (SD-classification) using summary indices of nutritional status: weight-for-age, height-for-age and weight-for-height were done. Normal test of proportions, Chi-square test for testing association of nutritional status with different characteristics and risk analysis using odds ratios with 95% confidence intervals was also done. Among all under five children surveyed, 36.4% underweight (<2SD weight- for -age), 51.6% stunted (<2SD height- for- age), and 10.6% wasted (<2SD weight- for- height). Proportions of underweight (45.5%) and stunting (81.8%) were found maximum among children aged 13-24 months. Wasting was most prevalent (18.2%) among children aged 37-48 months. Initiations of breast-feeding after six hours of birth, deprivation from colostrums and improper complementary feeding were found to be significant (P<0.05) risk factors for underweight. Wasting was not significantly associated (P>0.10) with any infant feeding practice studied. ICDS benefits received by children failed to improve the nutritional status of children. They concluded that delayed initiation of breast-feeding, deprivation from colostrums, and improper weaning are significant risk factors for undernutrition among under-fives. There is need for promotion and protection of optimal infant feeding practices for improving nutritional

Martens (2007) studied into the Impact of School Feeding Programme in Ghana with the aim of determining the nutrient intake from school meals and the out school food consumption of the children and the impact on demand for locally produced foods. Data were collected in 4 primary schools in 4 different districts in Central Region in Ghana from February to April 2007 with the study population of 129 3rd grade children aged 7 to 16 years.

Anthropometric measurements were taken to determine nutritional status. Data collection on nutrient intake from school meals was done using 1-day weighed dietary records and weighing the portion sizes of the selected 3rd grade children. The primary caretakers of the 3rd grade children were interviewed by trained translators using 24hr recalls to determine the out-school food consumption. The demand for locally produced foods per district was determined via the production figures of staple foods gathered from the district Agricultural Extension Service and the information from the weighed dietary records. The food composition data were derived from 3 tables, of which the leading table was: 'Table de composition d'aliments du Mali' (Barikmo, 2004) (supplements: 'Foods commonly used in Ghana' (Eyeson, 1975) and the 'NEVO table' (NEVO 2006)). The statistical is comprised of descriptive analyses on all data, ANOVA followed by a Tukey test for normally distributed variables, Kruskal-Wallis followed by a Dunnett test for skewed variables, a Spearman correlation test, an independent sample T-test and a paired sample T-test.The total food consumption had a DDS of 6.4 (±1.0), which is on average 1 (±0.8) food group higher than the home food consumption (sig. 0.001). Only 22.6% of the children still received a home lunch. The nutrient intake recommendations for energy (30-45% of RDA) and protein (60-70% of RDA), formulated by the Ghana SFP National Secretariat have been met (31.9% and 67.6% respectively). The iron intake (6.1±5.8) is low compared to the weighted DRI of this age group of 22.9 mg/day (bioavailability of 5%). The demand for locally produced staples is on average 0.07% of the total production of staples in the district. This may potentially increase to 1.11% in the year 2010.

The Ghana SFP succeeded in increasing the dietary diversity of the diet of the school children in the selected schools. This may reflect in the nutritional adequacy and nutritional status of the primary school children, bet no internationally agreed upon cut-off points are available to use as a reference. The Ghana SFP meets their recommendations for energy intake and protein intake. Vitamin A intake is probably sufficient, but the iron intake remains low, which raises concern. The impact of the Ghana SFP on the local demand for staple foods at district level seems limited.

Maseta et al (2008) conducted a comparative cross-sectional study to compare childcare practices and nutritional status of children aged 6–36 months in Mwembesongo and Mjimpya wards that had long and short experiences respectively with the Child Survival, Protection and Development (CSPD) programme. The purpose of the study was to establish whether the long-term implementation of the CSPD programme had an impact compared to that of a short-term programme. The findings showed that the children from Mwembesongo were exclusively breast-fed for a significantly longer period (50 days) than those in the Mjimpya ward (32 days) and that significantly more mothers (95.7%) in Mwembesongo than in Mjimpya (84.5%) attended growth monitoring programmes. On the other hand, significantly more mothers in Mjimpya (71.5%) compared to those in Mwembesongo (51.8%) breast-fed immediately (less than one hour) after birth. The study revealed that there was no significant difference in children's nutritional status (wasting and underweight) between the two wards, except for stunting. More children in Mwembesongo (39.7%) than in Mjimpya (27.5%) were stunted. The findings have demonstrated that financial capacity to support children's food and care requirements forms a springboard from which to launch additional efforts for improved nutritional status.

Janet and Mabel (1992) used Demographic Health Survey data I Malawi to assess the association between breast-feeding practices, socio-economic and morbidity variables, and the nutritional status of children under the age of five years using multilevel models. About 27% of under-five children in Malawi are underweight, and nearly 50% are stunted. The results of this study suggest that socio-economic factors, morbidity, and inappropriate feeding practices are some of the factors associated with malnutrition in Malawi. High socio-economic status, as measured by urban residence, the presence of modern amenities, and some maternal education, is associated with better nutritional status, whereas morbidity within two weeks before the survey is associated with low weight-for-age Z scores. Breast-feeding is almost universal and is carried on for about 21 months, but the introduction of complementary food starts much too early; only 3% of Malawian children under the age of 4 months are exclusively breastfed. Children aged 12 months or older who were still breastfeeding at the time of the survey were of lower nutritional status than those who had stopped breastfeeding. The analysis also showed a significant intra-family correlation of weight-for-age Z scores of children of the same family of about 39%.

In his study to the causes of morbidity and mortality in developing world, Adam (2005) identified under-nutrition and infection as the major causes. These two problems are interrelated. Under-nutrition compromises barrier function, allowing easier access by pathogens, and compromises immune function. Thus malnutrition predisposes to infection. Studies done worldwide by UNICEF indicate that Africa has the worst nutritional status with high levels of underweight, stunting and wasting countrywide (UDHS 2000 - 2001 and 1995). UNICEF also estimated that 40% of all deaths among children under five years of age were related to malnutrition, with high levels of underweight up to 12%. The general objective of this study was to assess the nutritional status of children under five years of age in Rweibaare Parish, Bushenyi District. A descriptive cross-sectional study using quantitative data collection methods was used to collect data from mothers or caretakers of 215 children under five years. A structured questionnaire was used to collect the data and anthropometric measurements (weight and height) were taken and recorded in a table. The measurements were transformed into the standard anthropometrical measurements and standard indices of physical growth were considered. The data collected was analyzed manually using frequency tables. The results revealed that the rate of malnutrition was high, of the 21 5 children assessed 32% of the children were stunted, 13% underweight and 2.8% wasted. The factors contributing to this were likely to be related with socio-economic status of the mothers which included age of the mother, education level and main occupation. Lack of information about nutrition was also a contributing factor as evidenced by inadequate breastfeeding with children that stopped breast feeding at four months and below having a high likelihood of malnutrition. Chronic malnutrition was a predominant form of malnutrition in this study as seen by malnourished children being mostly stunted (32%) and underweight (13%). Nutrients requirements are high and the diets given are often inadequate because of lack of suitable food, parental poverty, ignorance and the social customs to which they are subjected. One of the most striking problems facing the World Health Organisation is the high morbidity and mortality rates in infants and under fives, (WHO 2002). Under nutrition is described as the most pervasive human problem especially in less developed countries. It has an adverse effect on the quality of life and social and economic development (Gabir 1995). The problem of under nutrition is most prevalent among vulnerable groups especially in developing countries notably among children, adolescents, pregnant and lactating women and people living in difficult situations, such as the landless, the displaced and the poor (MOH 2002). In Uganda, as in other developing countries children below five years of age have been the target groups for nutrition programmes due to the high rates of mortality and morbidity in this age group.

UNICEF (1998), reported that the infant mortality rate was 97/1,000 live births and the under five mortality rate was 141/1,000 live births in Uganda. Thirty to forty percent of the children under five years of age are malnourished, 38% in the same age group are stunted 5% wasted, and 61% of the population living below the poverty line, (UDHS 1995). Despite the apparent abundance of food in Uganda, subsistence agriculture, the favorable climate, and enormous natural resources, malnutrition still exists. This is due to regional food imbalances due to ecological differences between the various regions of the country, the under-developed inter-regional food marketing system, poor road network and inadequate food processing and storage facilities. The nutritional status of children is influenced by both diet and frequency of infections. Under-five children have high mortality rates; they suffer from frequent infections such as malaria, measles, intestinal worms and skin diseases, (Jelliffe, 1996). It was therefore, concluded that malnutrition is a significant problem in Rweibaale Parish Bushenyi district. It can also be concluded that malnutrition is caused by many factors hence a need for a multi-sectoral approach if the problem is to be solved. The results could also be an indicator of a need for reproductive health services especially in planning for their families, caring for their children and have a source of income. It is therefore, recommended that another study be done to cover whole District to give a broader picture of nutritional status of children since this study covered only one Parish. Other studies that would use other indicators in addition to what was used (height and weight) such as upper arm circumference and head circumference is necessary. Health workers should be trained and re-oriented to do growth monitoring and promotion of good nutrition as part of integrated management of childhood illnesses.

According to Khaled (2009), Major progress has been made over the last 30 years in reducing the prevalence of malnutrition amongst children less than 5 years of age in developing countries. However, approximately 27% of children under the age of 5 in these countries are still malnourished. His work focuses on the childhood malnutrition in one of the biggest developing countries, Egypt. The study examined the association between bio-demographic and socioeconomic determinants and the malnutrition problem in children less than 5 years of age using the 2003 Demographic and Health survey data for Egypt. In the first step, separate geoadditive Gaussian models with the continuous response variables stunting (*height-for-age*), underweight (*weight-for-age*) were used, and wasting (*weight-for-height*) as indicators of nutritional status in the case study. In a second step, based on the results of the first step, we apply the geoadditive Gaussian latent variable model for continuous indicators in which the 3 measurements of the malnutrition status of children are assumed as indicators for the latent variable “nutritional status”.

2.5 An environmental intervention to prevent excess weight gain

Newton RL et al (2010) conducted a pilot study to examine the influence of an environmental intervention to preventing excess weight gain in African-American children using single-group repeated measures. An intervention was delivered to a school composed of African-American children. Approximately 45%of a total of 77 of enrolled second through sixth grade students were used in their study. The 18-month intervention was designed to alter the school environment to prevent excess weight gain by making healthier eating choices and physical activity opportunities more available. Body mass index percentile was the primary outcome variable. Body mass index z score was also calculated, and percent body fat, using bioelectrical impedance, was also measured. Total caloric intake (kilocalories) and percent kilocalories from fat, carbohydrate, and protein were measured by digital photography. Minutes of physical activity and sedentary behavior were self reported.

Mixed-models analysis was used with covering baseline values. Boys maintained, whereas girls increased, percent body fat over 18 months ($p = .027$). All children decreased percent of kilocalories consumed from total and saturated fat and increased carbohydrate intake and self-reported physical activity during the intervention ($p < .025$). Body mass index z score, sedentary behavior, and total caloric intake were unchanged.

The program may have resulted in maintenance of percent body fat in boys. The percent body fat in girls steadily increased, despite similar behavioral changes as boys. School-based interventions targeting African-American children should investigate strategies that can be effective across gender.

Zulfikar et al (2012) review of community-based antenatal, intrapartum, and postnatal intervention trials in developing countries aimed to identify (1) key behaviors and interventions for which the weight of evidence is sufficient to recommend their inclusion in community-based neonatal care programs and (2) key gaps in knowledge and priority areas for future research and program learning. Available published and unpublished data on the impact of community-based strategies and interventions on perinatal and neonatal health status outcomes were reviewed. Evidence was summarized systematically and categorized into 4 levels of evidence based on study size, location, design, and reported impact, particularly on perinatal or neonatal mortality. The evidence was placed in the context of biological plausibility of the intervention; evidence from relevant developed-country studies; health care program experience in implementation; and recommendations from the World Health Organization and other leading agencies.

A paucity of community-based data was found from developing-country studies on health status impact for many interventions currently being considered for inclusion in neonatal health programs. However, review of the evidence and consideration of the broader context of knowledge, experience, and recommendations regarding these interventions enabled us to categorize them according to the strength of the evidence base and confidence regarding their inclusion now in programs. This article identifies a package of priority interventions to include in programs and formulates research priorities for advancing the state of the art in neonatal health care.

The review emphasizes some new findings while recommending an integrated approach to safe motherhood and newborn health. The results of this study provide a foundation for policies and programs related to maternal and newborn health and emphasize the importance of health systems research and evaluation of interventions. The review offers compelling support for using research to identify the most effective measures to save newborn lives. It also may facilitate dialogue with policy makers about the importance of investing in neonatal health.

According to Daniels et al (2009) Primary prevention of childhood overweight is an international priority. In Australia 20-25% of 2-8 year olds are already overweight. These children are at substantially increased the risk of becoming overweight adults, with attendant increased risk of morbidity and mortality. Early feeding practices determine infant exposure to food (type, amount, frequency) and include responses (eg coercion) to infant feeding behavior (eg. food refusal). There is correlational evidence linking parenting style and early feeding practices to child eating behavior and weight status. A focus on early feeding is consistent with the national focus on early childhood as the foundation for life-long health and well being. The NOURISH trial aims to implement and evaluate a community-based intervention to promote early feeding practices that will foster healthy food preferences and intake and preserve the innate capacity to self-regulate food intake in young children.

This randomized controlled trial (RCT) aims to recruit 820 first-time mothers and their healthy term infants. A consecutive sample of eligible mothers will be approached postnatally at major maternity hospitals in Brisbane and Adelaide. Initial consent will be for re-contact for full enrolment when the infants are 4-7 months old. Individual mother- infant dyads will be randomized to usual care or the intervention. The intervention will provide anticipatory guidance via two modules of six fortnightly parent education and peer support group sessions, each followed by six months of regular maintenance contact. The modules will commence when the infants are aged 4-7 and 13-16 months to coincide with establishment of solid feeding, and autonomy and independence, respectively. Outcome measures will be assessed at baseline, with follow up at nine and 18 months. These will include infant intake (type and amount of foods), food preferences, feeding behavior and growth and self-reported maternal feeding practices and parenting practices and efficacy. Covariates will include socio demographics, infant feeding mode and temperament, maternal weight status and weight concern and child care exposure.

Despite the strong rationale to focus on parents' early feeding practices as a key determinant of child food preferences, intake and self-regulatory capacity, prospective longitudinal and intervention studies are rare. This trial will be amongst to provide Level II evidence regarding the impact of an intervention (commencing prior to age 12 months) on children's eating patterns and behaviors.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

Repeated measurement analysis sometimes known as longitudinal studies are used in many fields of study and the need to analyze this unique data is growing increasingly. Sometimes a distinction is drawn between longitudinal designs (where subjects are followed for extended periods of time) and repeated measures designs (where the measurements are collected over a relatively short period) (Ware, 1985).Repeated measures designs come in several forms such as split-plot, change over, sources of variability, and longitudinal studies. Split plot designs are mostly used in agricultural experiments where the field is split into multiple plots. Such plots are treated with different fertilizer, and crops are randomly assigned to the subplots within each fertilized plot (Kotz & Johnson, 1988). Each fertilized plot will produce several types of crops and a measure of each will be collected, yielding repeated measures for each plot. Change over designs may be used when testing two types of drugs. With this type of design, selected people are usually put into two groups with half given drug A and the others given drug B. Then drug A and drug B are switched and the experiment is rerun. This design is a repeated measures experiment because every person will have two measures, one for drug A and one for drug B (Kotz& Johnson, 1988). Source of variability studies may include taking several randomly selected items from a manufacturing process and allowing several people to test each one, possibly over several days (Kotz& Johnson, 1988). Longitudinal studies address situations such as the growth of chicks, where weights of each chick may be measured every few days. Usually, in longitudinal designs, the observational units are sampled over an extended period of time. However, there exists a subset of longitudinal designs where time is not an independent variable

(Ware, 1985). In this case, the interest is studies that are not broken into intervals of time but rather are categorized according to variables composed of concepts, items, or locations in space (Kotz& Johnson, 1988).

3.2 Model 1: (Where Every Subject Is Tested At Every Level)

In the need to test the efficacy of a drug in a clinical experiment, two methods of experimentation are available. First, an experimenter may collect observations on $N = I \times J$ people, randomly assign i^{th} of them to one of j^{th} treatment groups, and give each treatment group a different dose of the drug. Under this design, exactly one reading per person is taken. Alternately, an experimenter could collect observations on i^{th} person and test it at each of the j^{th} levels of the factor. This second method is categorized as repeated measures because the same set of people is used in multiple tests. The repeated measures experimental design is beneficial as it eliminates the variation due to subjects, which can significantly reduce the mean square error, ultimately making detecting real differences between the treatment doses easier (Montgomery, 1984).

In this Model, we will simulate an experiment with J treatments and I people. Each person is tested once per treatment, which helps minimize the amount of variation due to the subjects. This sort of study is used in many fields; one such example is in the field of psychology where several subjects were asked to read a set of sentences (Lorch& Myers, 1990). Each sentence was timed, so each subject provided multiple readings. In this particular model, we have I subjects with indices $i = 1, 2, 3, \cdots, I$ in our experiment with j^{th} repeated measures per person with indices $j = 1, 2, 3, \cdots, J$ person is timed as they read J sentences, and a time is recorded for each sentence. Let $N = I \times J$ denote the total number of observations.

In Model 1, y_{ij} is the measurement of the time it took the i^{th} person to read the j^{th} sentence. In this example, X_1 will be a dummy coded variable for which sentence is being read. But in other experiments, X_1 could just as easily be a continuous variable, such as the dose of a drug taken for a study. Other independent variables may exist as well, such as the age of the person, gender, or IQ score, denoted $X_2, X_2, \cdots, X_k$, however, only one independent variable is used in these simulations. **β** is a vector of the coefficients, and **ε** is the vector of errors. Let **Σ** be the covariance matrix of the errors.

The model will be of the form:

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \qquad 3.1$$

where X is a matrix of the independent variables, β is the vector of the coefficients, and ε is the vector of errors

In matrix notation we have:

$$y = \begin{bmatrix} y_{11} \\ y_{12} \\ \vdots \\ y_{1j} \\ y_{21} \\ \vdots \\ y_{ij} \end{bmatrix}, \quad X = \begin{bmatrix} 1 & x_{11} & \cdots & x_{k1} \\ 1 & x_{12} & \cdots & x_{k2} \\ \vdots & \vdots & & \vdots \\ 1 & x_{1j} & \cdots & x_{kj} \\ 1 & x_{11} & \cdots & x_{k1} \\ \vdots & \vdots & & \vdots \\ 1 & x_{1j} & \cdots & x_{kj} \end{bmatrix}, \quad \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix}, \quad \varepsilon = \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{12} \\ \vdots \\ \varepsilon_{1j} \\ \varepsilon_{21} \\ \vdots \\ \varepsilon_{ij} \end{bmatrix}$$

$$\Sigma = \begin{bmatrix} \mathrm{cov}(\varepsilon_{11},\varepsilon_{11}) & \mathrm{cov}(\varepsilon_{12},\varepsilon_{11}) & \cdots & \mathrm{cov}(\varepsilon_{1j},\varepsilon_{11}) & \mathrm{cov}(\varepsilon_{21},\varepsilon_{11}) & \cdots & \mathrm{cov}(\varepsilon_{ij},\varepsilon_{11}) \\ \mathrm{cov}(\varepsilon_{11},\varepsilon_{12}) & \mathrm{cov}(\varepsilon_{12},\varepsilon_{12}) & \cdots & \mathrm{cov}(\varepsilon_{1j},\varepsilon_{12}) & \mathrm{cov}(\varepsilon_{21},\varepsilon_{12}) & \cdots & \mathrm{cov}(\varepsilon_{ij},\varepsilon_{12}) \\ \vdots & \vdots & \ddots & \vdots & \vdots & & \vdots \\ \mathrm{cov}(\varepsilon_{11},\varepsilon_{1j}) & \mathrm{cov}(\varepsilon_{12},\varepsilon_{1j}) & \cdots & \mathrm{cov}(\varepsilon_{1j},\varepsilon_{1j}) & \mathrm{cov}(\varepsilon_{21},\varepsilon_{1j}) & \cdots & \mathrm{cov}(\varepsilon_{ij},\varepsilon_{1j}) \\ \mathrm{cov}(\varepsilon_{11},\varepsilon_{21}) & \mathrm{cov}(\varepsilon_{12},\varepsilon_{21}) & \cdots & \mathrm{cov}(\varepsilon_{1j},\varepsilon_{21}) & \mathrm{cov}(\varepsilon_{21},\varepsilon_{21}) & \cdots & \mathrm{cov}(\varepsilon_{ij},\varepsilon_{21}) \\ \vdots & \vdots & & \vdots & \vdots & \ddots & \vdots \\ \mathrm{cov}(\varepsilon_{11},\varepsilon_{ij}) & \mathrm{cov}(\varepsilon_{12},\varepsilon_{ij}) & \cdots & \mathrm{cov}(\varepsilon_{1j},\varepsilon_{ij}) & \mathrm{cov}(\varepsilon_{21},\varepsilon_{ij}) & \cdots & \mathrm{cov}(\varepsilon_{ij},\varepsilon_{ij}) \end{bmatrix}$$

It is also noted that these matrices were created for a regression analysis. If RM ANOVA is utilized, which requires categorical variables, the **X** matrix must be adjusted.

In this model, the **X** matrix used for RM ANOVA would have two categorical variables, which would be dummy coded with J - 1 levels for the treatments and I - 1 dummy coded variables for the subjects and result in rank(**X**) = (J - 1) + (I - 1) + 1. Figure 3.1 shows how data from such a model would look if graphed, where each observational unit is given its own symbol. For example, if there was a study on a blood pressure drug the graph could look as following, where a patient (denoted +,×,○, or ♦) has three blood pressure readings taken, one at each dosage of a drug (maybe 1, 2, and 3mgs).

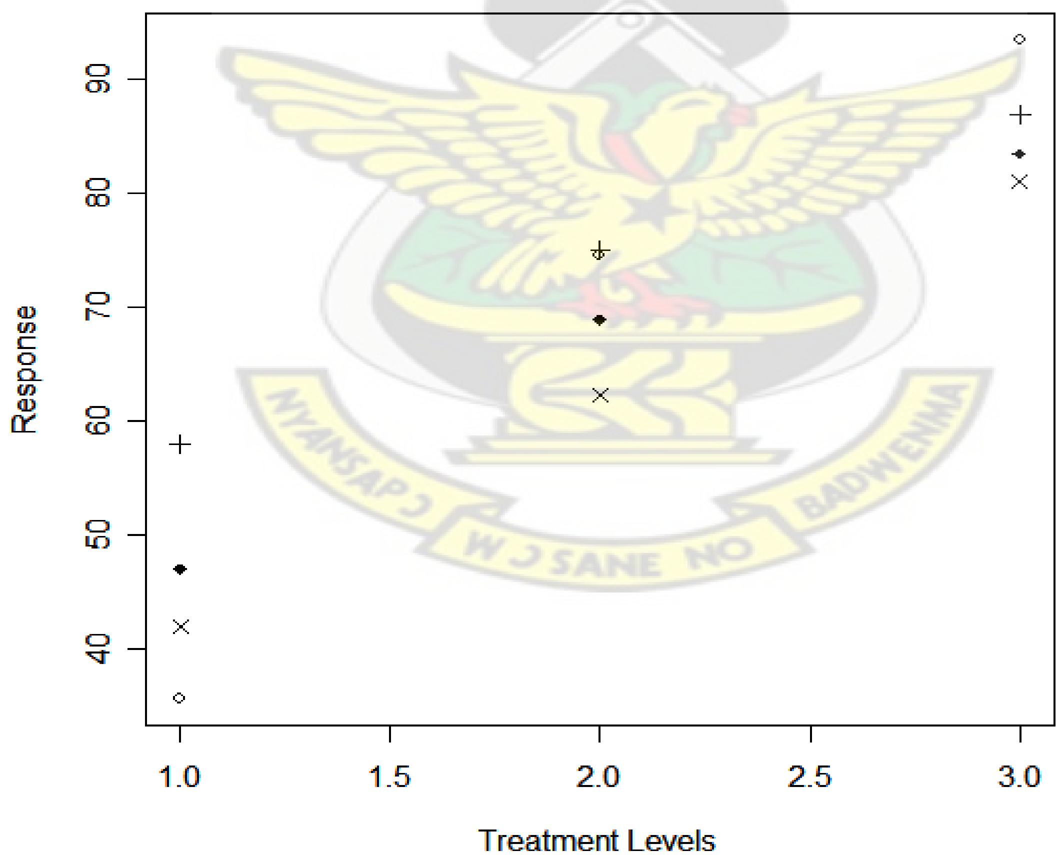


Figure 3.1 **Graphical Representation of Model 1**

Crowder and Hand (1990) describe many inefficient methods of analyzing this experiment type. These methods include performing multiple t-tests on different groupings of the factors and observational units. This analysis tends to be invalid because the involvement of multiple hypothesis tests increase the chance of a Type I error (Bergh, 1995). Others suggest performing multiple regressions on these crossover design experiments, allotting one regression for each observational unit. Some suggest performing an area under the curve analysis, but this examination only inspects one very specific feature of the regression curve. Similarly, other aspects like time to the peak, half-life of the curve, or distance back to the baseline are not accounted for (Crowder & Hand, 1990). Crowder and Hand (1990) suggest the best way to analyze data is to have one all-inclusive ANOVA or regression model, so as not to have multiple statistical tests.

3.3 Repeated Measures Analysis of Variance (ANOVA)

In Model 1, each measurement on a subject is taken at each of the levels of treatment. Therefore, if, as before, an experimenter wanted to test a drug's effectiveness he or she could simply test each person at, for example, J = 3 dosage levels. All subjects must be tested at all treatment levels for repeated measures ANOVA (RM ANOVA) to be a valid test (Montgomery, 1985). The null hypothesis is that effectiveness is statistically the same at each treatment level (Misangyi et al., 2006). If the F value is large enough, then the null hypothesis will be rejected, and the treatments will be considered statistically distinct. The calculations for the F values as shown in Table 3.1 is given as

$$F = \frac{MSTR}{MSE} \qquad 3.2$$

$$F = \frac{MSBS}{MSE} \qquad 3.3$$

MSTR is mean square treatment, MSBS is mean square between subject and MSE is mean square error.

The interest is in the first F value in the above equations because that is used to test the null hypothesis that the treatments levels are the same. This analysis is identical to randomized complete block design with subjects as the blocks (Montgomery, 1985).

3.1 ANOVA with One Within-Subject Factor

Sources	*df*	*SS*	*MS*	*F*
Between Subject	*i-1*	*SSBS*	*MSBS*	*MSBE/MSE*
Within subject	*i(j-1)*	*SSWS*	*MSWS*	
Treatment	*J-1*	*SSTR*	*MSTR*	*MSTR/MSE*
Error	*(j-1)(i-1)*	*SSE*	*MSE*	
Total	*IJ-1*	*SST*		

In a standard ANOVA setting, without repeated measures, all of the error terms are assumed independent and normally distributed, with equal variance. Also, in ANOVA, the independent variable is considered as a factor variable that contains levels. In RM ANOVA, since the variation broken into two parts, one due to the observational units and one due to the factor levels, the assumptions must be modified. Because the assumptions of independence and constant variance no longer necessarily hold, and this assumption is change to one of sphericity, or circularity, which restricts the variances and correlations of the measurements (Bergh, 1995). Compound symmetry, a condition where all variances of the factor levels are equal and all covariances between each pair of factor levels are equal (O'Brien & Kaiser, 1985), can be examined in place of the less restrictive sphericity assumption because, if it does not hold, the sphericity assumption usually will not hold. First, the variance of each level of the factor must be identical so as not to violate the assumptions. For example, we may test children at ages 2, 4, 6, and 8; with sphericity it is assumed that the correlation between observations taken at ages 2 and 4, and the correlation between observations taken at ages 4 and 6 would be the same. Usually, it would not be the case that the correlation between observations taken at ages 2 and 8 is the same as the correlation between observations taken at ages 2 and 4, but compound symmetry requires this supposition (O'Brien & Kaiser, 1985). The sphericity assumption generally will be violated when individuals are being tested over a time range or more than two measurements are taken: two characteristics of most longitudinal designs (O'Brien & Kaiser, 1985). In this way, the sphericity assumption is almost always violated in the repeated measures situation making RM ANOVA (O'Brien & Kaiser, 1985) and may lead to an increase in Type I errors if the degrees of freedom are not adjusted (Misangyi et al., 2006).

In the previous sentence reading example, a possibility arises that some people may start to read each successive sentence at an accelerated pace as they become familiar with the topic; thus their rate of increase is not necessarily constant. This acceleration could cause the variance of the time to read each sentence to increase over the whole group and thus violate the sphericity assumption (Misangyi et al., 2006).

Some researchers suggest performing a series of tests for sphericity. This is done by defining a special covariance matrix (Σ_T) of the treatment levels $\left(T_j\right)$ in Model 1 such that:

$$\Sigma_T = \begin{bmatrix} \text{var}(T_1) & \text{cov}(T_1, T_2) & \cdots & \text{cov}(T_1, T_J) \\ \text{cov}(T_2, T_1) & \text{var}(T_2) & \cdots & \text{cov}(T_2, T_J) \\ \vdots & \vdots & \ddots & \vdots \\ \text{cov}(T_J, T_1) & \text{cov}(T_J, T_2) & \cdots & \text{var}(T_J) \end{bmatrix}$$

We can examine an estimate of this covariance matrix to verify the supposition of sphericity in the repeated measure situations. Compound symmetry is defined as constant variance and covariance of Σ_T (Baguley, 2004). Compound symmetry is a stricter form of sphericity, and therefore, if compound symmetry holds, the sphericity assumption is met. Unfortunately, sphericity can also be met by a much more general rule, so we must verify that the variances of the differences between each factor level T_v and T_m are equivalent (Baguley, 2004) for every set of *v* and *m*, using the formula:

$$\operatorname{var}(T_v - T_m) = \operatorname{var}(T_v) + \operatorname{var}(T_m) - 2\operatorname{cov}(T_v, T_m) \qquad 3.4$$

If the differences of the variances for all of the treatments are equivalent, sphericity will hold (Baguley, 2004). As long as the sphericity assumption is met, the *F* test does not need adjustment because it will not be biased. An RM ANOVA test would suffice only if the sphericity condition were met (Cornell, Young, Seaman, & Kirk, 1992). When the sphericity assumption is violated the *F* test will have a positive bias and we would be more likely to reject the null hypothesis when it is true (Misangyi et al., 2006). O'Brien and Kaiser (1985) noted that in many cases, sphericity may fail when repeated observations are taken on a subject since those observations are correlated. In these cases, we are prone to assume the model is significant when, in reality, it is not (Misangyi et al., 2006). To avoid all of the problems with violations of sphericity, it is suggested that a less powerful multivariate analysis (MANOVA) be performed because these tests do not have an assumption about sphericity (Bergh, 1995).

Cornell et al. (1992) compared eight different types of tests for sphericity. The most commonly employed and discussed test for sphericity is the *W* test, also known as Maulchly's likelihood ratio test. This test has been shown to be rather futile because it does not work well with small sample sizes or in cases where Normality is in question (O'Brien & Kaiser, 1985). The *W* test also tends to be too conservative for light-tailed distributions and too liberal for heavy-tailed distributions (Crowder & Hand, 1990). Another test for sphericity is the *V* test, a locally best invariant test, which has been shown to be slightly superior to the *W* test (Cornell et al., 1992). The other possible tests are the *T* test, a ratio of the largest to smallest eigenvalues of the sample covariance matrix (Σ_T), and *U* tests one through five, based on Roy's union intersection principle. Cornell et al. (1992) ran simulations, compared these tests, and found that, in most cases, the *V* test is most powerful in detecting sphericity. However, other authors suggest not using any of these tests because they do not provide enough information and often are faulty (O'Brien & Kaiser, 1985). Because most authors agree that nearly all repeated measures experiments fail to meet the sphericity assumption, we assume an initial test for sphericity is not useful (O'Brien & Kaiser, 1985). When the experimental data fails the sphericity test and thus violates the assumptions of regression or RM ANOVA, a Box's epsilon (ϵ) correction on the degrees of freedom is commonly used (Box, 1954). Box described the correction on the degrees of freedom but never derived a formula for ϵ, so others have provided a variety of implementations for estimates of this correction factor. These correction factors, called Box's epsilon estimates, reduce the degrees of freedom of the RM ANOVA *F* test (Quintana & Maxwell, 1994).

We can perform the RM ANOVA and then calculate a Box's epsilon value to correct the biased *F* test, making the test for sphericity no longer necessary. The Box's epsilon estimate is multiplied by the degrees of freedom yielding new smaller degrees of freedom values and adjusting the *F* test (Crowder & Hand, 1990). In Model 1, the usual degrees of freedom associated with ANOVA would be J - 1 and (J - 1)(I - 1). Our new degrees of freedom then are:

$v_1 = e(J-1)$ and $v_2 = e(J-1)(I-1)$. We would use the *F* value found for the ANOVA but then compare this to an *F*-critical value using the corrected degrees of freedom (Misangyi et al., 2006). In all cases, ϵ should never be greater than one, and if the sphericity assumption is met, then $\epsilon = 1$. Most estimators of ϵ are biased, because they can produce values greater than one and must be restricted to a domain of [0, 1] (Huynh & Feldt, 1976).

Greenhouse and Geisser (1958) suggest a set of conditions for the viability of the *F* test instead of checking the sphericity assumption or performing a Box's epsilon correction (Crowder & Hand, 1990). They argue that the *p*-value for the ANOVA being tested will only get larger with all of these adjustments. If the *p*-value is already large, we can retain the null hypothesis with confidence, even though the assumptions of sphericity may be violated. However, if the *p*-value is small, we can check the limit of the critical value $F(1, I * J - 1)$. If the *p*-value is still small, we can reject the null hypothesis with confidence. Now, the only cases remaining are when:

$$F_{\alpha,1,I*J-1} < F_{observed} < F_{\alpha,J-1,(J-1)(I-1).}$$

In this case, we must test for sphericity and use a Box's epsilon correction or abandon the ANOVA test altogether (Huynh & Feldt, 1976).

Returning to the problem with sphericity tests, a Box's epsilon adjustment can be used to assess the deviation from the sphericity assumption. If a Box's epsilon estimate is approximately equal to one, we can conclude that the sphericity assumption is not violated (Baguley, 2004). Alternately, if a Box's epsilon estimate is less than one, sphericity is violated. However, we will only adjust the degrees of freedom with a Box's epsilon estimate if sphericity is seriously violated; in this case a Box's epsilon estimate is less than 0.75.

Several people have proposed different Box's epsilon estimates. Importantly, of the models examined in this research the assumption about sphericity and these estimated corrections only apply to Model 1 because the design is balanced and the contrasts are orthonormal (Crowder & Hand, 1990). One of the most commonly used Box's epsilon estimators was constructed by Greenhouse and Geisser and this is given by

$$\varepsilon = \frac{\left(tr\left(\Sigma_T\right)\right)^2}{(J-1)\,tr\left(\Sigma_T^2\right)} = \frac{\left(\sum_t^{J-1} \lambda_t\right)^2}{(J-1)\sum_t^{J-1} \lambda_t^2} \qquad 3.5$$

where Σ_T is the estimated covariance matrix of the J - 1 orthonormal contrasts, and λ_t are the J - 1 eigenvalues of Σ_T (Greenhouse & Geisser, 1958). Greenhouse and Geisser's epsilon tends to be too conservative but adjusts well for the Type I error rate (Quintana & Maxwell, 1995). Huynh and Feldt(1976) proposed a correction, denoted (HF or ε), to the Greenhouse and Geisser Box's epsilon as follows :

$$\varepsilon = \min\left(1, I\left(J-1\right)\varepsilon - 2/\left(J-1\right)\left[I-1-\left(J-1\right)\varepsilon\right]\right) \qquad 3.6$$

Some statistical software such as GentStat has included these two Box's epsilon estimators because they are so commonly used (O'Brien & Kaiser, 1985).

Quintana and Maxwell (1995) performed simulations and comparisons of eight possible Box's epsilon corrections. To the two Box's epsilon estimators already mentioned, they also advocated a correction by Lecoutre, denoted by ε^*, when two or more groups are part of the experiment (Quintana, 1995). After much study, Quintana and Maxwell (1995) concluded that the most precise correction factor, however, uses either ε or ε^* depending on the value of ε^*; and no correction factor works well on data sets with small sample sizes. Much of the time with RM ANOVA a correction on the degrees of freedom is necessary. Most people find the more common ε or ε correction and use them to adjust the degrees of freedom. A less powerful MANOVA analysis might be used, which would not need the sphericity assumption because the only assumption made is that the data arises from a multivariate Normal distribution where the variances and covariances are unstructured (Misangyi et al., 2006). However, the multivariate approach will not work when more treatment levels than subjects exist in the experiment because the covariance matrix will be singular (Crowder & Hand, 1990). Looney and Stanley suggest running two analyses, one univariate and one multivariate, by halving the tolerance level on each test. In our simulations, we use ε as our correction factor because it is most commonly employed and fairly accurate. We also track the number of times the Box's epsilon correction is below 0.75 because researchers suggest that this is the threshold for determining whether sphericity was violated or not (Misangyi et al., 2006).

3.4 Longitudinal Data Models

Longitudinal data is used to study the pattern of change and the factors that influence those changes both within and between subjects. Subjects could be individuals, animals, and or plants that act as their own controls. Longitudinal data requires special statistical methods because the set of observations on one subject tend to be intercorrelated.

This inter-correlation must be accounted for to make a valid inference. Another goal is to investigate the effects of important covariates on the patterns of change. There are two types of patterns: Non-time varying covariates, which could be gender or age and are considered between (fixed) effects. Time varying covariates such as weight, time or income are considered within (random) effects (Pahwa and Blair, 2002). In measuring the mean response, we use the formula

$$\mu_{it} = E\left(Y_{it}\right) \quad 3.6$$

and seeing how it changes over time will be the primary goal and the secondary goal will be to draw conclusions about the parameters that summarize the characteristics of the covariance or correlation among the repeated measures.

From the equation 3.6, the mean response is allowed to vary over time (which can be seen by its dependence on the subscript *t)* and changes in the mean response can be related to the individual levels of covariates because of its dependence on the subscript *i*.

3.5 Notation

Let Y_{it} be the response for the i^{th} subject $(i = 1, 2, ..., N)$ at the t^{th} occasion where $(t = 1, 2, ..., n_i)$. The total number of subjects is equal to $\sum_i^N n_i$, $y_i = n_i \times 1$ is the vector of responses, and $X_i = p \times 1$ is the covariate vector for subject *i* at time *t*. The matrix of covariates is $X_i = n_i \times p$ for subject *i* and will usually include an intercept. For example in a 14 repeated measures data with four factors, if *i* = *subject*, $t = 1, \cdots, 14$ (number of repeated measures), $y_i = 14 \times 1$, $x_{it} = 4 \times 1$ and $X_i = 14 \times 4$. If the fixed effects are age and gender because they do not change throughout the duration of the study and the within individual effects are time and body weight, the data set will be a balanced with time. This meaning that all subjects will be measured at a common set of occasions and there will be no missing data.

3.6Covariance Structures

Although modeling the correlation structure is not of primary importance repeated measure analysis it is still however necessary to take into consideration any correlation that may exist when making statistical inference about longitudinal data. Correlation among subjects will probably come from three sources of variability: a) between subject effects, b) within subject effects and c) measurement errors (Fitzmaurice, Laird, and Ware, 2004). An analysis is not valid unless the covariances among the repeated measures are modeled properly.

There are several structures that can be used in the analysis of correlated data with the unstructured (UN) being one of the most commonly used structures. The unstructured structure allows the elements of the covariance matrix to be unconstrained (there are no assumptions being made about the variance and the covariance). This structure is not constrained to be nonnegative definite in order to avoid non linear constraints and therefore it must be symmetric and positive definite. The covariance matrix $Cov(Y_i) = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_2^2 & \sigma_{23} & \cdots & \sigma_{2n} \\ \sigma_{31} & \sigma_{32} & \sigma_3^2 & \cdots & \sigma_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \sigma_{n3} & \cdots & \sigma_1^2 \end{bmatrix}$ states that the variances across individuals and the correlations are different. This structure is less powerful when there is missing data and/or when the size of the sample is not large enough to estimate an unstructured covariance (the data must be large enough to estimate the $\frac{n(n+1)}{2}$ covariance parameters).

Another popular structure is the compound symmetry (CS) $Cov(Y_i) = \begin{bmatrix} 1 & \rho & \rho & \cdots & \rho \\ \rho & 1 & \rho & \cdots & \rho \\ \rho & \rho & 1 & \cdots & \rho \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho & \rho & \rho & \cdots & 1 \end{bmatrix}$

where $\rho \geq 0$ is the only constraint. This structure states that the correlations between all pairs of measures are the same and the variance is constant across occasions. The compound symmetry is very useful when the mean response is dependent on some combination of population parameters and a single random effect. The biggest disadvantage is its assumption that the correlations between any pair of measurements are the same regardless of time and the variance is constant. Typically, consecutive measurements that are made closer together are more correlated than those that are farther apart. The assumption that the variance is constant is also not valid within longitudinal studies.

The auto regressive (1) [AR (1)] structure $Cov(Y_i) = \begin{pmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{n-1} \\ \rho & 1 & \rho & \cdots & \rho^{n-2} \\ \rho^2 & \rho & 1 & \cdots & \rho^{n-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^{n-1} & \rho^{n-2} & \rho^{n-3} & \cdots & 1 \end{pmatrix}$ resolves some of the objections the compound symmetry has with successive data and when the measures are equally spaced over time. The AR (1) structures states that the variance is constant and the correlations between two responses that are *t* measurements apart are ρ^t where $\rho \geq 0$. With this structure, the correlations decrease over time, which is assumed to happen in longitudinal data but most longitudinal studies will not decrease as fast. This structure is only appropriate when the measurements are made at equal time intervals.

The Toeplitz TOEP covariance structure $Cov(Y_i) = \begin{pmatrix} \sigma^2 & \sigma_1 & \sigma_2 & \cdots & \sigma_n \\ \sigma_1 & \sigma^2 & \sigma_1 & \cdots & \sigma_{n-1} \\ \sigma_2 & \sigma_1 & \sigma^2 & \cdots & \sigma_{n-2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_n & \sigma_{n-1} & \sigma_{n-2} & \cdots & \sigma^2 \end{pmatrix}$

assumes pair of responses that are equally spaced in time have the same correlation and the variance does not have to be constant. This structure is also only valid when the measurements are taken at the same time intervals.

The first order factor analytic without the diagonal matrix D can be used when the structure is nonnegative definite. When the number of random factors is less than the dimension of the matrix ($q<t$), the structure is nonnegative. This structure can be used to approximate the unstructured matrix in the random statement, where q is equal to the number of random effects.

The variance component VC structure is the default structure for the random and repeated statements used in the mixed models. When used in the random statement a separate variance component is assigned to each effect and when used in the repeated statement, it will specify a heterogeneous variance model. All of the above models can be used with the constraint that the variance is heterogeneous which is true in most longitudinal studies. Ignoring the correlation can cause the inferences about the regression parameters to be incorrect, the estimates of β will be inefficient, and there will be no protection against biases, which is caused by missing data.

2.7 Advantages and Disadvantages

There are several advantages and disadvantages to using longitudinal studies.

Some of the advantages are: subjects serving as their own controls which mean the direct study of change can be measured; fewer subjects are required because the measurements are being repeated, between-subject variation is excluded from the error, and longitudinal data can separate aging effects from cohort effects. Some of the disadvantages are: the dependence of the measurements which must be accounted for in the analysis, models are not as well developed;

the risk of attrition, carry-over effects, and the improvement or the decline could be caused by treatment or fatigue.

3.8Univariate repeated measure analysis

There are three main approaches to analyzing longitudinal data:

- Marginal Analysis: where the mean of the response is of importance
- Random Effects Models: used to determine how the regression coefficients change over the individuals
- Transitional Models: where its main focus is to determine how the response variable for a specific subject at time *t* depends on past values of the response and other variables.

Marginal Models focus on the average of the response variable and how that average changes over time. For the data set used in this thesis using marginal models would answer the question: Does the average lever pressing behavior change over time and does age, gender, bodyweight, and time influence those changes?

A simple analysis of longitudinal data is done by the univariate repeated measures ANOVA. The ANOVA is used to compare and estimate groups in terms of their means and their trends over time. There are several assumptions that must be met in order to use the repeated measures ANOVA.

⇒ The data and errors are normally distributed

⇒ The group comparisons are not used to explain individual growth

⇒ There is no missing data

⇒ The data must also be balanced

If these assumptions are not met the results may be inaccurate.

3.9Univariate Repeated Measure Model

In the univariate repeated measures ANOVA the correlation is assumed to come from the individual specific random effects; this is due to the fact that each subject is assumed to have an underlying level of response that persists over time and influences all measurements on that subject. The times of measurement are treated as a within-subject factor and the effect of time is assumed to be the same for all subjects. The response for the i^{th} subject is assumed to be related to discrete covariates and is assumed to be different from the population mean μ.

Repeated measures ANOVA can be expressed

$$y_{ij} = \mu + \tau_i + V_j + e_{ij}\,,\ \begin{cases} i = 1,2.\cdots s \\ j = 1,2,\cdots t \end{cases} \qquad 3.8$$

where $E(Y_{ij}) = X_{ij}^{'} = \mu + V_j$

The parameter v_j is the effect of time. The parameter $\tau_i \approx N(0, \delta_\tau^2)$ is the random subject effect that gives the between-subject variance, and $e_{ij} \approx N(0, \delta_e^2)$ is a within-subject measurement error and it gives the within-subjects variance. The covariance matrix of the ANOVA has a compound symmetry structure, where the variance and covariance are homogeneous across time and equal to $\dfrac{\delta_\tau^2}{\delta_\tau^2 + \delta_e^2}$

3.10 MULTIVARIATE ANALYSIS OF VARIANCE (MANOVA)

3.10.1 Preview

Multivariate analysis of variate (MANOVA) is an extension of the univariate analysis of variate (ANOVA) to accommodate two or more dependent variables. MANOVA is a technique that measures the differences for two or more metric dependent variables base on the set of categorical variables acting as independent variables.

Like ANOVA, MANOVA is concerned with differences between groups or experimental treatments. MANOVA is termed multivariate procedure because it is used to assess group difference across multiple metric dependent variables simultaneously. In MANOVA, each treatment is observed on two or more dependent variables.

The concept of multivariate analysis of variance was introduced more than seventy (70) years ago by Wilks (1932). However, it was not until the development of appropriate test statistics with table distributions and more recent wide spread availability of computer programs to compute the statistics that it became a practical tool for researchers.

3.10.2 Multivariate Procedure for Assessing Group Difference

As statistical inference procedure, both the univariate techniques (t test and ANOVA) and their multivariate extensions (Hotelling T^2 and MANOVA) are use to assess the statistical significance of difference between groups. In the t test ANOVA the null hypothesis tested is the equality of single dependent variable means across groups. In multivariate techniques, the null hypothesis tested is the equality of vectors of means on multiple dependent variables across groups. The differences between the hypotheses tested in both cases are shown below:

$$H_o : \mu_1 = \mu_2 = \mu_3 = \cdots = \mu_n \tag{3.9}$$

Null hypothesis H_o = all the group means are equal, that is they come from the same population. This is for the univariate analysis of variance case.

For the multivariate analysis of variance (MANOVA), the null hypothesis H_o is stated as follows:

$$H_o : \begin{bmatrix} \mu_{11} \\ \mu_{21} \\ \\ \\ \mu_{p1} \end{bmatrix} = \begin{bmatrix} \mu_{12} \\ \mu_{22} \\ \\ \\ \mu_{p2} \end{bmatrix} = \ldots\ldots\ldots \begin{bmatrix} \mu_{1k} \\ \mu_{2k} \\ \\ \\ \mu_{pk} \end{bmatrix} \tag{3.10}$$

Unlike the ANOVA, a variate is tested for equality in MANOVA and the researchers actually have two variates, one for the dependent variables and another for the independent variables. The dependent variable variate is of more interest because the metric-dependent measures can be combined in a linear combination as in multiple regression and discriminant analysis. The uniqueness of MANOVA is that the variate optimally combines the multiple dependent measures into a single value that maximizes the differences across groups.

3.10.3 The Two-group MANOVA

Assume that we have two groups of multivariate observations, as in the example above, and that there is n_1 observations in group 1 and n_2 observations in group 2. Hence we observe the $p-vectors$ y_{ij}, $j = 1, 2, \cdots, n_1, i = 1, 2, \cdots, n_2$, or equivalently expressed, we observe the $(n_1 + n_2) \times p$ matrix Y. Formally, the statistical model that underlies the MANOVA is "just" an ANOVA model for each variable together with an error structure that allows for covariance between response variables:

$$y_{ij} = \mu_i + e_{ij} \tag{3.11}$$

For $i = 1, 2, \cdots n_1$ and $j = 1, 2, \cdots n_2$

where, if the number of variables equals three: $p = 3$

$$\mu_1 = \begin{pmatrix} \mu_{11} \\ \mu_{21} \\ \mu_{31} \end{pmatrix} \text{and } \mu_2 = \begin{pmatrix} \mu_{12} \\ \mu_{22} \\ \mu_{32} \end{pmatrix} \qquad (3.12)$$

are the two expected group means. As in univariate ANOVA, we interested in an overall statistical significance test for the hypothesis of no group difference at all

$$H_0 : \mu_1 = \mu_2$$
$$H_1 : \mu_1 \neq \mu_2$$

Note, that this hypothesis expresses that the groups are equal in all the response variables, and that the alternative expresses that in at least one variable there is a group difference. So this is a composite hypothesis jointly in all variables. Computationally, the analysis is handled by computing the group and overall mean:

$$\overline{y_1} = \frac{1}{n_1}\sum_{j=1}^{n_1} y_{1j}, \qquad \overline{y_2} = \frac{1}{n_1}\sum_{j=1}^{n_2} y_{2j} \qquad 3.11$$

$$\overline{y} = \frac{1}{n_1 + n_2}\sum_{i=1}^{2} n_i \overline{y_i} \qquad 3.12$$

the (weighted) between group variance-covariance structure of these averages:

$$SS_{Between} = \sum_{i=1}^{2} n_i \left(\overline{y}_i - \overline{y}\right)\left(\overline{y}_i - \overline{y}\right)^T$$

and the within-group covariances of the group-corrected data:

$$SS_{Within} = \sum_{i=1}^{2}\sum_{j=1}^{n_i}\left(\bar{y}_{ij} - \bar{y}_i\right)\left(\bar{y}_{ij} - \bar{y}_i\right)^T$$

From a statistical perspective, the two group centroids are estimates of the unknown group centroids μ_1 and μ_2 and the within group error variance-covariance matrix Σ is estimated as

$$\Sigma = S_w = \frac{1}{n_1 + n_2 - 2} SS_{within}$$

(3.13)

in analogy with the univariate case. From the example above it is clear that the key information about the group differences is given by the distance between the two centroids. This difference can be measured statistically by the Mahalanobis distance:

$$MD^2 = (\bar{y}_1 - \bar{y}_2) S_w^{-1} (\bar{y}_1 - \bar{y}_2)^T \qquad (3.14)$$

Recall, how this distance measure down weighs directions in which there is a high residual variability and up weighs directions of low residual variability (allowing for covariances between each variable). In the case of two groups the MD^2 related to the multivariate generalization of the student's *t-test*, Hotelling's T^2 as:

$$T^2 = \frac{n_1 n_2}{n_1 + n_2} MD^2 \qquad (3.15)$$

and the T^2 can be transformed into an exact F-ratio as follows:

$$F = \frac{n_1 + n_2 - p - 1}{2\left(n_1 + n_2 - p\right)} T^2 \qquad (3.16)$$

which has an F-distribution with p and $n_1 + n_2 - p - 1$ degrees of freedom (under the null hypothesis). Multivariate confidence ellipsoids for group mean and/or mean difference can be found from the F-distribution and the inverse within group covariance matrix S_w^{-1}.

3.10.4 The Multiple group one-way MANOVA

Assume that we have Igroups of multivariate observations with n_i observations in group *i*, $i = 1, 2.\cdots, I$. Hence we observe the $p - vectors$ y_{ij}, $i = 1, 2, \cdots, n_i$, $j = 1, 2, \cdots, I$. The model is expressed exactly as for the two-group case:

$$y_{ij} = \mu_i + e_{ij}, \ \mathrm{var}\left(e_{ij}\right) = \Sigma \tag{3.16}$$

For $i = 1, 2.\cdots, I$ and $j = 1, 2, \cdots, n_i$

The hypothesis of no group difference at all is given as

$$H_0 : \quad \mu_1 = \cdots = \mu_I \tag{3.20}$$

with the alternative that for at least on variable there is at least two groups that differ. Again, this is a composite hypothesis jointly in all variables, even to a higher degree than for the two-group case, since it is composite in as well the group structure as in the variables.

Computationally, the analysis is handled exactly as above. First the averages are computed as;

Treatment mean

$$\overline{y}_1 = \frac{1}{n_1} \sum_{j=1}^{n_1} y_{ij}$$

And the total mean as

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{I} n_i \bar{y}_i \tag{3.17}$$

where $n = n_1 + n_2 + \cdots, n_I$.

Then the between-group information is found:

$$SS_{Between} = \sum_{i=1}^{I} n_i (\bar{y}_i - \bar{y})(\bar{y}_i - \bar{y})^T \tag{3.18}$$

and the within-group covariance of the group-corrected data:

$$SS_{Within} = \sum_{i=1}^{I}\sum_{j=1}^{n_i}\left(\bar{y}_{ij} - \bar{y}_i\right)\left(\bar{y}_{ij} - \bar{y}_i\right)^T \tag{3.19}$$

And as before the group means are estimates of the unknown group mean μ_i and the within group error variance-covariance matrix Σ is estimated as

$$\Sigma = S_W = \frac{1}{n-I} SS_{Within} \tag{3.20}$$

In the univariate hierarchy of methodology *the F-test* is introduced as a necessary tool when going from two to more than two groups. This is because there is no direct generalization of the *t*-statistic (a difference between two groups) to more than two groups, since e.g. three groups require two distances to summarize the group difference information. So instead of comparing the (two) groups directly they are all compared with the overall mean/centroids of the data, that is, the between group variation. In the univariate case, the *F*-statistic has the form (assuming for a moment that the ***SS***'s are univariate)

$$F = \frac{SS_{Between} / df_{Between}}{SS_{Within} / df_{Within}} \tag{3.21}$$

In the multivariate case the measure of group differences in the light of the within-group variability is given by the matrix

$$SS_{Within}^{-1} \times SS_{Between} \tag{3.22}$$

In fact the unique decomposition of the total variability often expressed in the univariate case also holds for multivariate: $SS_{Total} = SS_{Between} + SS_{Within}$

(3.23)

Where SS_{Total}

$$SS_{Total} = \sum_{i=1}^{I} \sum_{j=1}^{n_i} \left(\overline{y}_{ij} - \overline{y}\right)\left(\overline{y}_{ij} - \overline{y}\right)^T \tag{3.24}$$

The exercise of doing a statistical hypothesis test for the hypothesis of no group differences is to evaluate the degree of extremeness of this statistic compared to what would be expected under the null hypothesis. Due to the multivariate nature, extremeness can be defined in various ways. Four of these are usually standard output from statistical software:

$$Pillai, s\,Trace = \sum_{k=1}^{K} \frac{\lambda_k}{1 + \lambda_k}$$

$$Hotelling, s\,Trace = \sum_{k=1}^{K} \lambda_k$$

$$Wilk's \ \Lambda = \prod_{k=1}^{K} \frac{1}{1+\lambda_k}$$

$$Roy's \, Largest \, Root = \frac{\lambda_{\max}}{1+\lambda_{\max}}$$

Where $\lambda_1, \lambda_2, \cdots \lambda_K$ are the eigenvalues of the $SS_{within}^{-1} \times SS_{Between}$ matrix. The number of eigen values K is equal to the minimum of the dimension of the variables space and the number of groups minus 1, $K = \min(p, I-1)$. Being familiar with PCA a way to express this would be: Perform a PCA on the $S_w^{-1/2}$ pre-processed group average data and compare the explained variances of each component with what comes out of data where the groups are truly equal. Note that eigenvalues are the variations of the principal directions of the variables that are corresponding to the covariance matrix $SS_{Between}$. In other words the first (largest) eigenvalue of this matrix express the largest possible variation (between group means) of a new combined variable (the first principal component). The largest eigenvalue of $SS_{within}^{-1} \times SS_{Between}$ expressed the largest possible variation between group means taking the within-covariance (point scatter shape) into account.

The theoretical null hypothesis distribution of these statistics is in principle known and described in the literature. However, often they are substituted by approximate *F*-ratios. We give here no formulas for these approximations. However in the two group case all of these statistics are equivalent and can be exactly equivalently expressed by the *F*-ratio and/or Hotelling's T^2.

In Sharma (1995), Olson (1974) is referred to as showing that the Pillai's Trace was the most robust and had adequate power to detect true differences under different conditions, and hence Pillai's Trace is recommended to test multivariate significance.

3.11The Multivariate Repeated Measures Model

To illustrate the procedure consider the following 3-level model for two measurements

$$y_{ijk} = \delta \sum_{I} \beta_{IK}^{(1)} X_{ijk}^{(1)} + (i - \delta) \sum_{I} \beta_{IK}^{(2)} X_{ijk}^{(2)} + \delta e_{jk}^{(1)} + (1 - \delta) e_{jk}^{(2)} \tag{3.25}$$

δ =1 *if measurement* 1, *otherwise* 0

where *i* refers to the measurement, *j* refers to occasion and *k* refers to individual subject. The terms under the summations include both fixed and random terms, the latter for example including polynomial terms in age with random coefficients. Level 1 has no variation and we need to specify the covariance structure at level 2 which is the between-occasion level.

The level 3 variation is that across individual subjects. If we regard the level2 (within subject) variation as composed of measurement error and essentially random fluctuations then we may use this level 3 variation as the basis

CHAPTER FOUR

DATA COLLECTION, ANALYSIS AND RESULTS

4.1 Introduction

This chapter seeks to examine the data collected for the study in the study area, the analysis of the collected data and the presentation of results. Table 4.1 presents the snapshot of the data used for the analysis. It was collected from two hundred and ten (210) children less than five years of which 70 were at exclusively breastfeeding stage (0-6 months), 70 breastfeeding with introduction Plumpy nut food (7-12 months) and also 70 children between the ages of13-18 months who were in complementary feeding stage. The data for the study was a primary data from weighing centers in Tamale metropolis. The children were observed for a period of six months.

The table is made up of 14 columns. Column one represents the study identity number of the children, column two the ages in months, column three the sex of the children, column four represents birth position of the child with column five representing the number of siblings living with the child. Occupation of the mother is in column six, column seven is the feeding type with feeding practice of the children in column eight. The repeated weighing records for the six months are shown in columns 9 – 13 respectively. In the data there were three feeding type studied. These are:

i) Exclusive breastfeeding represented by the number 1 in column 6 of the data in appendix

ii) Breastfeeding with the introduction of Plumpy nut food supplements represented by the number 2 in column 6 of the data in appendix

iii) Complementary feeding group represented by the number 3 in column 6 of the data in appendix

Row 1 to row 70 contained data for the children with ages 0 – 6 months old, rows 71 to 140 represents those of ages 7 – 12 months old and the rest of the seventy rows were the ages 13 – 18 months. Equal group size was used satisfy the assumption of group equal in repeated measure analysis. All the three feeding groups were included in the analysis to examine weight change within them in the study period.

Table 4.1Snapshot of the Data Used For the Analysis

ID	Age	Sex	posi	sib	Occ	Feed	prac	W1	W2	W3	W4	W5	W6
1	1	2	1	1	3	1	1	3.0	4.0	4.5	4.4	4.5	5.0
2	1	2	1	1	3	1	1	3.2	4.5	5.6	6.6	6.7	6.9
3	1	1	4	3	2	1	1	2.8	5.3	6.0	7.0	6.9	7.5
4	1	2	3	3	3	1	1	4.8	5.5	6.0	6.2	6.6	6.7
.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.
71	2	2	2	2	1	2	2	5.0	6.2	6.0	6.2	6.5	6.7
72	2	1	3	3	1	2	2	4.4	5.1	5.5	6.0	6.2	5.8
73	2	1	2	2	1	2	2	6.0	6.3	5.9	6.8	7.3	7.2
.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.
207	3	1	1	1	2	3	2	8.0	8.2	8.8	9.0	9.5	10.0
208	3	1	1	1	2	3	2	5.1	5.8	6.0	6.5	7.0	7.0

209	3	1	2	1	3	3	2	6.5	6.5	7.1	7.3	8.6	8.0
210	3	1	3	2	2	3	2	8.5	8.5	9.0	9.7	10.2	10.8

4.2 Descriptive Statistics

The weight of the children was measured repeatedly over the six months to determine if age, sex, child birth position, number of siblings living with the child, mother's occupation, feeding type and feeding practices were factors that affects the weight gain of the children. The random samples of 210 children (n=70 each for the three age groups and the three feeding types) with (105 each of male and female) in 6 observations each, for a total of 1260 observations were studied. The mean age weights of the children were 4.738 (0-6 months), 6.297 (7-12 months) and 7.441 (13-18 months). The mean weight gained over the time period by sex were 6.182 (female children) and 6.136 (male children) suggesting an insignificant difference in weight gain by gender. With the feeding types, breast feeding with the introduction of Plumpy nut food supplement produces a mean weight of 6.293, the complete complementary feeding type had a mean weight of 7.441 and the exclusive breast feeding group had a mean of 4.738.

Occupation of mothers did not also show a significant change in mean weight over the six months at 6.173, 6.191, and 6.114 respectively for government employee, house wife and trader. Factors such as number of siblings and position of birth of child to the mother were also shown insignificant with mean weight gains as 6.110, 6.200, 6.392 and 5.895 respectively for first born, forth born second born and third born to their mothers and 6.130, 5.993, and 6.237 respectively for no sibling, 2 siblings and 1 sibling living with the child. Another factor that will be influencing the weight gain is the child feeding practices in the house. These produces a mean weight of 7.453 representing child self feeding, 5.573 exclusively by the mother and 6.568 representing the mother and other relatives.

4.3 Profile Plot for Mean Weight Gain for Age Groups at Each Month

Profile plot of mean responses in repeated measurement analysis can be very useful as there provide a good basis for selecting a suitable models for the data set. Figure 4.1 displays a plot of the mean weight gain at each month for each age group. The red line in the figure represent the age group 13-18, the green line represent 7-12 months children while the black line represent 0-6 months children.

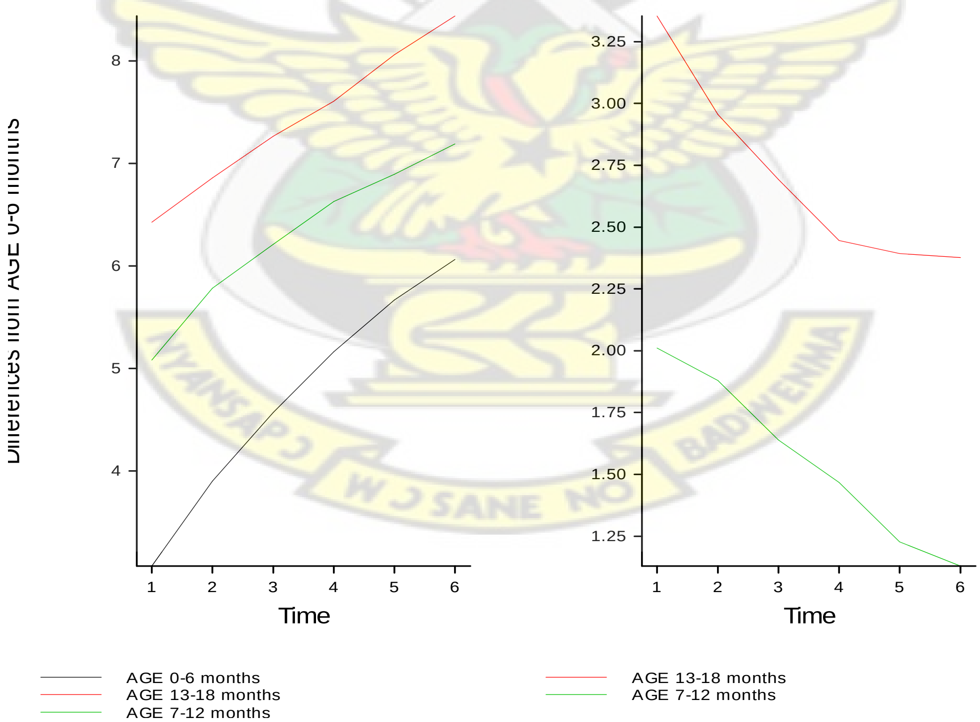


Figure 4.1 Mean Weight Gain for Age Groups at Each Month

Measuring the differences in mean response over time is more like measuring within individual weight change of the children (Fitzmaurice, laird, and ware, 2004). From the figure it can be deduced that the mean weight of the age group 0-6 months grew faster than the other two age groups even though there were all increasing over the time period. The growth rate of the age group observed a slight decrease in the mean weight gain from the second month to some where month five. The graph also suggest a within individual weight gain effect agreeing to the earlier on suggestion from the mean analysis.

4.4 Profile Plot for Mean Weight Gain for the Feeding Types at Each Month

Figure 4.2 also shows a plot of the mean weight gain at each month for each of the three feeding types.

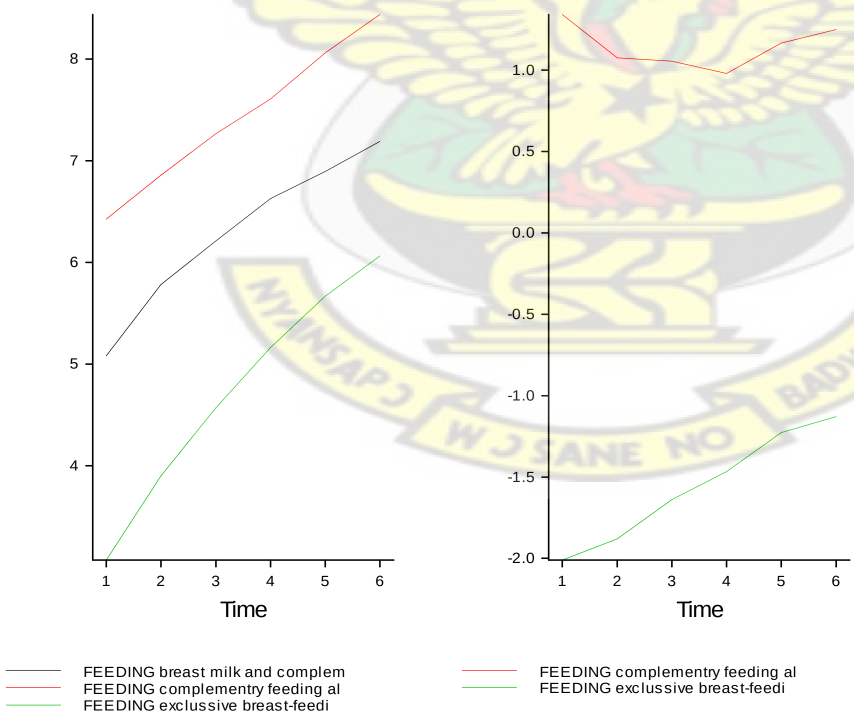


Figure 4.2 Mean Weight Gain for the Feeding Types at Each Month

The three groups realized a different rate of increase in weight gain from the start of observation to the end. The observation in this is similar to the age group observation made above. This may be because the three age groups where fed with different food types. The graph also suggest a within feeding type difference over the six months period.

4.5 Profile Plot for Mean Weight Gain for Gender at Each Month

The mean weight gain at the various months within for each gender was also plotted as shown in figure 4.4. The black line represents female while the red line represents male.

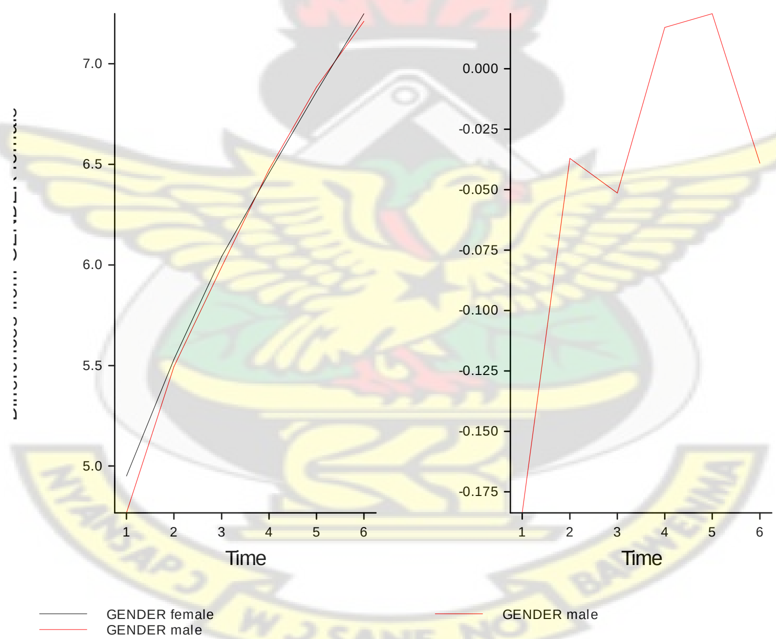


Figure 4.4 Mean Weight Gain for Gender at Each Month

The graph shows the female children growing at a rate slightly higher than their male counterpart at the beginning up to month 3 and slightly lower than the male children after the month 5. In general the mean weight gain was similar for gender over the study period. Another areas where different groups shows similar mean weight gain were for occupation of the mother, birth position of child and number of siblings living with the child. Figures 4.5, 4.6, and 4.7 in appendix A shows these respectively

4.6 INFERENTIAL STATISTICS

To archive the set objectives of the study, repeated-measures analysis of variance techniques were used for the analysis with the response variable been the weight of the children. There are two main options used in the analysis of repeated measurement from a given subject;

Option 1: Using Repeated-Measures ANOVA, the Univariate approach. This option has restrictive assumptions.

Option 2: Using Repeated-Measures MANOVA, the Multivariate approach. This approach has less restrictive assumptions.

The tests were done with the level of significance of 5% (CI = 95%). The results from the various analyses performed was obtained using the GenStat software package (version 12) and IBMSPSS (version i9) on a Pentium IV PC with Windows 7 operating system which implements both the univariate model and the multivariate model.

4.6.1 Assumptions of the Models

- ⇒ Both repeated measure ANOVA and MANOVA assume that the time intervals are equally spaced
- ⇒ Both methods assumed that the response is normally distributed. The approaches however are robust against violation of normality assumptions
- ⇒ Repeated measure ANOVA sphericity, or required compound symmetry which is:
- ⇒ The variance of the response variable must be the same at each time point

$\Rightarrow$ The correlations between repeated measurements are equal, regardless of the time interval between measurements.

4.6.2 Univariate Analysis

Univariate analysis of repeated measures has three approaches to analyzing longitudinal data set.

- Marginal analysis where the mean responses is of interest
- Random Effects Models. This is how the regression coefficients change over time is determined.
- Transitional models. Here the main focus is to determine dependence of the response variable for a specific subject at time t on past values of other variables

In Univariate repeated measures ANOVA the correlation is assumed to come from the individual specific random effect because each subject is assumed to have an underlying level of responses that persists over time and influences all measurement on that subject. The times of measurement are treated as a within-subject factor and the effect of time is assumed to be the same for all subjects. The i^{th} subject response is assumed to be related to discrete covariates and is assumed to be different from the population mean μ.

The univariate analysis of repeated measures model can be written as

$$y_{ij} = \mu + \tau_i + V_j + e_{ij}$$

$$i = 1,2,....,t \quad and \quad j = 1,2,....,s$$

Where τ_i is the i^{th} Age effect and given by $t\left(\bar{y}_{i\cdot} - \bar{y}_{\cdot\cdot}\right)^2$ for each time point, and V_j is the j^{th} time point effect given by $s\left(\bar{y}_{\cdot j} - \bar{y}_{\cdot\cdot}\right)^2$ for the factor age. The table 4.2a and 4.2b shows the print out of the between subjects effect and the within subject effect of the model. The tables are made up of six columns each. The source of variation column, the degree of freedom column, sum square column, mean square column, expected mean square and the p-value columns

Table 4.2a Univariate Analysis of variance for between Subject Effects

Test of Hypotheses for Between Subject Effects					
Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
Subject stratum					
AGE	2	1546.4401	773.2201	136.26	<.001
Residual	207	1174.6069	5.6744	29.08	
Total	209				

In the table 4.2a, the results shows the age as been significant with the p – value of <.001 at α = 0.05 level of significance. This means that the hypothesis that the weight gains by age groups are the same over the time period would be rejected. Weight of a child therefore changes as he or she grows from one month to the other.

In table 4.2b, the above equation can be written as

$$y_{ij} = \mu + \tau_{Age} + V_{Time} + \left(\tau V\right)_{Age \bullet Time} + e_{ij}$$

With the Subject.Time stratum degree of freedom correction factor of 0.4988, the model produces results as follows

Table 4.2bUnivariate Analysis of variance for within Subject Effects

UnivariateTest of Hypotheses for Within Subject Effects					
Source of variation	**d.f.**	**s.s.**	**m.s.**	**v.r.**	**F pr.**
Subject.Time stratum d.f. correction factor 0.4988					
Time	5	814.9137	162.9827	835.29	<.001
Time.AGE	10	34.1982	3.4198	17.53	<.001
Residual	1035	201.9498	0.1951		
Total	1259	3772.1087			

The hypothesis for the age groups by time interaction is also significant since the hypothesis that the interaction has no effect on weight gain produces a p – value <.001. It can therefore be concluded that the effect of both time and age is significant on weight gain by the children.

4.6.3 Univariate Analysis of Variance by Feeding Type over Time

In table 4.3a and 4.3b, the repeated measure ANOVA results for the dependent variable (weight gain by children) by feeding type as independent variable is also presented respectively for the within and between subjects effects.

Table 4.3a Test of Hypotheses for Between Subject Effects

Test of Hypotheses for Between Subject Effects					
Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
Subject stratum FEEDING Residual	 2 207	 1546.4401 1174.6069	 773.2201 5.6744	 136.26 29.08	 <.001
Total					

The between feeding effect test in the above table produces a p-value of < .001. This does not support the hypothesis of equal mean effects. Therefore the test for feeding type is also significant.

Table 4.3bUnivariate Analysis of variance for within Subject Effects

UnivariateTest of Hypotheses for Within Subject Effects					
Source of variation	**d.f.**	**s.s.**	**m.s.**	**v.r.**	**F pr.**
Subject.Time stratum d.f. correction factor 0.4988					
Time	5	814.9137	162.9827	835.29	<.001
Time.FEEDING	10	34.1982	3.4198	17.53	<.001
Residual	1035	201.9498	0.1951		
Total	1259	3772.1087			

In the within subject effect test above it is shown that feeding type by time interactions is significant at $\alpha = 0.05$ significance level with p-values 0.001

4.6.4Analysis of variance for gender

To perform the comparism test between male and female weight gain at the childhood level using the univariate analysis of variance model stated above, table 4.4a produce the results for the dependent variable (weight gain) by the independent variable (gender).

Table 4.4a Analysis Of Variance Table for Gender

Test of Hypotheses for Between Subject Effects					
Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
Subject stratum GENDER Residual	 1 208	 0.6446 2720.4023	 0.6446 13.0789	 0.05 57.96	 0.825
TOTAL					

The results shows that the between subject (gender) effect is not significant. This is because the p – value generated for the analysis is 0.825 greater than the α = 0.05 level of significance. Therefore we fail to reject the hypothesis that the mean weight gain is the same for the six months. Sex is not an influencing factor on growth at the infant level. This also confirmed the profile plot graph in figure 4.4 stated earlier.

Table 4.4bUnivariate Analysis of variance for within Subject Effects

Univariate Test of Hypotheses for Within Subject Effects					
Source of variation	**d.f.**	**s.s.**	**m.s.**	**v.r.**	**F pr.**
Subject.Time stratum d.f. correction factor 0.4473					
Time	5	814.9137	162.9827	722.25	<.001
Time.GENDER	5	1.4633	0.2927	1.30	0.275
Residual	1040	234.6847	0.2257		
Total	1259	3772.1087			

In table 4.4b the test present in-significant test for the gender by time interaction at 5% with the p – value of 0.275. It can therefore be concluded that the effect of both time and gender is not significant on weight gain by the children.

4.7Ante Dependence Analysis for Age

Below is the analysis of the treatment or interaction effects for each factor in the study area. There is a table for each factor. For each time point, there was a test for an effect at that time point, and another for an effect in all the data up to that time. The first column is the time with the statistic, degrees of freedom and its probabilities respectively for the test for an effect at that time point while the rest of three columns are for effect in all the data up to that time for age factor. Table 4.5 present the information.

Table 4.5Tests Of AGE Assuming Ante-Dependence Structure Of Order 5

Time	Statistics	d.f.	Probability	Statistics	d.f.	Probability
1	213.221	2	<0.001	213.221	2	<0.001
2	2.569	2	0.277	215.280	4	<0.001
3	2.944	2	0.229	217.715	6	<0.001
4	0.355	2	0.837	217.541	8	<0.001
5	10.666	2	0.005	227.779	10	<0.001
6	6.897	2	0.032	234.200	12	<0.001

It can be seen in table 4.5 that, for age factor, an effect has appeared at the first month and also at the fifth month and above. No effect was realized from month three and month four. The overall test statistic using all the data set from all the time point for the three different age groups was 234.200 at 12 degrees of freedom show a significant effect with a probability of 0.001 at the 0.05 significance level.

The feeding type by each time effect test shows similar results to that of the age groups above. The effects of the treatment were seen at the 1st month, the 5thmonth and the 6th month. There was no effect produce in the 2nd up to the 4th months. The overall test statistic of 234.200 at 12 degrees of freedom using all the data set from all the time point for the three different feeding groups also have a significant effect with a probability of 0.001 at the 0.05 significance level. Table 4.6in appendix A presents the distribution.

4.7.1Ante dependence Analysis for Gender

The gender ante dependence analysis shows a different analysis from that of age and feeding type. There was no effect of the treatment in all the months for the six months period. The overall test using all the data set from all the time point for the two gender levels was not significant since the overall test statistic as 6.699 at 6 degrees of freedom with the p-values of 0.350 far greater than 0.05. Table 4.4shows the print out.

Table 4.7Test for Change at Each Time and Overall Test Up To Each Time

Time	Statistic	d.f.	Probability	Statistic	d.f.	Probability
1	0.594	1	0.441	0.594	1	0.441
2	3.111	1	0.078	3.711	2	0.156
3	0.250	1	0.617	3.954	3	0.267
4	1.263	1	0.261	5.216	4	0.266
5	0.062	1	0.803	5.267	5	0.384
6	1.428	1	0.232	6.699	6	0.350

4.8Repeated measure Multivariate Analysis

At this stage of the analysis, other factors like feeding practice, birth position on the child, number of siblings living with the child and mothers occupation are considered leading to a multivariate analysis of the repeated measure analysis.

Using the output in table 4.9 the standard definition for the extremes are shown for the factors. The table contains seven columns and six rows. The effects of the factors are in the first column, the extremes for each factor is in column two, the values of the extremes in column three and *F* values in column four. Hypothesis degrees of freedom, error degrees of freedom and the significance are in column five, six, and seven respectively.

Table 4.9Multivariate Repeated Measure Analysis on Weight Gain

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.919	303.776	6.000	161.000	.000
	Wilks' Lambda	.081	303.776	6.000	161.000	.000
	Hotelling's Trace	11.321	303.776	6.000	161.000	.000
	Roy's Largest Root	11.321	303.776	6.000	161.000	.000
practice	Pillai's Trace	.356	5.840	12.000	324.000	.000
	Wilks' Lambda	.670	5.958	12.000	322.000	.000
	Hotelling's Trace	.456	6.075	12.000	320.000	.000
	Roy's Largest Root	.347	9.361	6.000	162.000	.000
Position	Pillai's Trace	.181	1.748	18.000	489.000	.029
	Wilks' Lambda	.828	1.752	18.000	455.862	.029
	Hotelling's Trace	.198	1.753	18.000	479.000	.028
	Roy's Largest Root	.121	3.297	6.000	163.000	.004
siblings	Pillai's Trace	.084	1.181	12.000	324.000	.296
	Wilks' Lambda	.918	1.176	12.000	322.000	.299
	Hotelling's Trace	.088	1.171	12.000	320.000	.303
	Roy's Largest Root	.058	1.570	6.000	162.000	.159
occupation	Pillai's Trace	.061	.847	12.000	324.000	.602
	Wilks' Lambda	.940	.846	12.000	322.000	.602
	Hotelling's Trace	.063	.845	12.000	320.000	.603
	Roy's Largest Root	.050	1.351	6.000	162.000	.238

The table shows that only the feeding practice is an influential factor in determining the weight gain of children less than five years. This is with the fact that the p-value for all the extreme measures is 0.000 at 5% significance level. This means that factors such as position of birth, number of sibling and mothers qualification do not directly influencing growth at the infant level.

4.9REML Variance Components Analysis

To estimate the covariance structure define for the random model, the restricted maximum likelihood variance component analysis was conducted. Table 4.10 present the results. The first part looked at the covariance structure define for the random model and the second part looked at the residual variance model.

Table 4.10REML Variance Components Analysis

Covariance structures defined for random model Covariance structures defined within terms:				
Term	Factor	Model	Order	No.rows
subject._Time	subject Time	Identity Uniform	1 1	210 6

Residual variance model					
Term	Factor	Model(order)	Parameter	Estimate	S.e.
$Subject \bullet Time$			Sigma2	1.108	0.093
	subject	Identity	-	-	-
	Time	Uniform	theta1	0.8240	0.0162

The restricted maximum likelihood analysis above present the covariance structure defined for the random model. The analysis estimated the Sigma2 which is the total variance for the experiment to be 1.108. Therefore the whole –plot error variance can be determine by finding the product of the total variance (Sigma2) and the value of the theta1 which is 0.8240. That is $1.108 \times 0.8240 = 0.9130$

Gender variance component analysis estimated the Sigma2 (the total variance) to be 2.368 and the theta1 as 0.9047. Therefore the whole –plot error variance can also be determine by finding the product of the total variance (Sigma2) and the value of the theta1 which is 0.9047. That is $2.368 \times 0.9047 = 2.1423$

4.9.1Wald Tests for Repeated Measure Fixed Effects

Table 4.11 below shows the output of the ANOVA for the Wald test for fixed effect. The table contained five columns representing the fixed tern, Wald statistic degree of freedoms, Wald mean sum of squares and the chi-square probabilities

Table 4.11 Wald Test for Fixed Effect

Fixed term	Wald statistic	d.f.	Wald/d.f.	Chi-sqprob
Sequentially adding terms to fixed model				
Time	4176.46	5	835.29	<0.001
AGE	272.53	2	136.26	<0.001
Time.AGE	175.27	10	17.53	<0.001
Dropping individual terms from full fixed model				
Time.AGE	175.27	10	17.53	<0.001

In the table we realized that all the three terms (time, age and the interaction between the time and the age) in the fixed model are significant with p-values 0.001. The test for gender fixed effects however present a different picture. Among the three fixed terms, time is only significant at 0.001probability. Gender and the interaction are not significant. The p-value for the two effects is 0.824 and 0.262 as shown in table 4.12 in appendix A

4.10 Repeated Measure Multiple Regression Model

To find out the relationship between monthly mean weight gain and factors such as position of child to the mother, number of siblings living with the child, mother's occupation and child feeding practice in the house,multiple regression analysis defined as:

$$y = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon$$

was performed. Where y is the dependent variable, $x_1, x_2, ..., x_k$ are the independent variables, $\beta_o, \beta_1, ..., \beta_k$ are the coefficients and ε is the error variable.

Table 4.13 contains the output of the regression analysis of variance with the model

$$Weight\ gain = 5.278 + 0.87_{siblings} + 0.220_{occupation} + 0.914_{feedingpractice} + error$$

The table had six columns; the first column is the model, column two is the sum of squares, column three the degree of freedoms and column five contain the value of the test statistic and the sixth column is the p-value

Table 4.13Regression ANOVA Output

Model		S S	Df	M S	F	Sig.
1	Regression	72.381	4	18.095	10.055	.000[a]
	Residual	368.940	205	1.800		
	Total	441.321	209			

a. Predictors: (Constant), Feeding practice of child, Number of siblings to the child, Occupation of mother, position of child to the mother

b. Dependent Variable: mean weight

From the table, it can be deduced that the model is significant with F-value of 10.055 at p-value of 0.00. The factor that contributed significantly to the weight gain was the feeding practice in the house. Number of siblings and occupation of the mother even though have positive coefficients (0.087 and 0.220) respectively, their contribution to the model is not significant ($p = 0.69$ and $p = 0.08$ respectively).

4.11 DISCUSSION OF RESULS

The study use a random sample of 210 children repeatedly for six months in the study area to find out whether the monthly weight of children recorded at the weighing centers in the metropolis are significantly different and if age and gender could contribute to the weight changes. The descriptive statistics of the mean monthly weight among the three age groups showed that, the children within the ages of 0-6 months (exclusive breast feeding group) had an average weight of 4.738and those of the age group 7-12 had the mean weight of 6.297.Those of within the ages 13-18 records an average growth of 7.441. The least significant differences of the means at 5% level for time, age and time × age interaction were 0.0847, 0.3241, and 0.3503 respectively showing that the corresponding differences in mean were significant for age. This suggests that growth of children is thus influence by age with the elderly growing at much faster than the newly born once. The standard errors of the differences of means for time, age and time × age interaction were recorded as 0.0431, 0.1644 and 0.1780 respectively with the interaction having the highest deviation. Closely related to the analysis of the average weight gain to the age was the feeding type. This was so because the type of food taking by infants at the early ages is determine by their ages.

The result also shows that the average weight gain of the children by sex was almost equal with the female gaining weight averagely of 6.182 slightly above their male counterpart of 6.136. The error deviation of the time was 0.0464 and that of the gender stood at 0.2038 with the time × gender interaction at 0.2124.

One useful plot in repeated measure analysis is that of the profile plot of mean responses. These plots provide the bases for the selection of suitable models for the data set. In figure 4.1, the mean weight gain at each time was plotted. The figure shows likely significant differences in weight gain among the three age groups over the period. A similar plot was seen with that of the feeding type in the house in figure 4.2. Plot for the mean weight by Gender did not show any clear difference as shown in figure 4.3

Two methods were used in the inferential analysis; the repeated-measure ANOVA, the univariate approach and the repeated-measures MANOVA, the multivariate approach. Both have similar assumption with the univariate approach been more restrictive. The data was analyzed using a Univariate repeated-measure model $y_{ij} = \mu + \tau_i + V_j + e_{ij}$

Where τ_i is the i^{th} Age effect and given by $t\left(\bar{y}_{i\cdot} - \bar{y}_{\cdot\cdot}\right)^2$ for each time point, and V_j is the j^{th} timepoint effect given by $s\left(\bar{y}_{\cdot j} - \bar{y}_{\cdot\cdot}\right)^2$ for the factor age. The print out in table 4.2 shows the analysis of variance table for the independent variable by Age of the children. The results reject the null hypothesis that the average weight gain is the same for the three age groups with the F ratio for the between subject (Age groups) equal 136.26. This followed the calculation:

$$F = \frac{SSBS/df}{SSE/df} = \frac{1546.4401/2}{1174.6069/207} = 136.26$$

The p- value for the outcome is < .001 which is significant at 5% level. The hypothesis of Age by Time interaction is also rejected with the p-value of < .001 concluding that the effect of both time and age on weight gain is significant.

In tables 4.3 and 4.4, the results explain a similar analysis for feeding type ANOVA and feeding practices with the null hypothesis been rejected in both cases. The F ratio for the feeding type was the same as the age groups and that of the feeding practice even though lower than that of the age and the feeding type was significant with the probability < .001.

In table 4.5, the between subject (gender) effect was not significant. The F ratio for the gender was equal to 0.05 with the F probability of 0.825 far greater than 5% level of significance. Therefore we fail to reject the null hypotheses that gender does not influence growth in children at the infant stage. The sex of the child is insignificant as far as growth is concerned. Time was significant but the interaction between time and gender was not significant.

Another analysis that was carried out was the ante dependence analysis for all the factors involves identifying which particular time point a given factor was significant. For the three age groups and that of the three feeding types, the effect appeared at the first month, the five and the seventh months. The total statistic using the all the data set from all the time point was 234.200 at 12 degrees of freedom showing a significant effect with a probability of 0.001 at 5% level. The ante dependence test for the feeding practice also observed a treatment effect at first month, the third month, the fourth month and that of the sixth month. There was no effect in the second and the fifth months. The overall test statistic was 88.669 with 12 degrees of freedom for all the data set from all the time point. This was also significant at the 5% level with the p-value of <.001. Table 4.8 present the distribution. Gender did not show any significant effect in all the time point for the six months and the overall test statistic was 6.699 at 6 degree of freedom. The p-value was 0.350 showing that it was not significant.

The analysis of variance from the MANOVA approach was used to determine the significance of the effects as suggested above. The time effect was significant since the p-value for it is 0.00 with the observed powers for all the test statistics to be 1.00.

The analysis also shows that the TIME * GENDER interactions were not significant since the p-value for that was 0.189 which is far above the 0.05 significance level. This suggests that the significance of the change in weight gain by children at their early stage of growth does not depend on the sex of the child. The significance of the change in the weight gain was however seen to be depending on the age group of the children. This was as a result of the significant test produced by the TIME * AGE interaction with a p-value of 0.00.

CHAPTERE FIVE

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The study was design to determine the significance of Time effect on the weight gain of children less than five years in the Tamale metropolis. Tamale metropolis constitutes about 13% of the entire Northern region of Ghana with a land area of 750 square kilometers. It has a population of 293,881, predominated by Dagombas.

The study used a sample of 210 children of three different age groups (0-6 months, 7-12 months and 13-18 months) of 105 each of male and female. Each age group has 70 children. Weights of the children were recorded on monthly basis repeatedly for six months totaling 1260 data points for the analysis.

Deductions made from the descriptive analysis were that, children within the group of 0-6months gained a monthly average weight increasing from 3.07 at the first month of the study to 6.06 in the sixth month with a monthly average of 4.859. Those within 7-12 months also recorded a monthly mean weight gain of 5.08 at the beginning of the study increasing to 7.19 at the end of the sixth month. The monthly average of this group was 6.297 and the last group (13-18) months had a monthly growth average of 6.42 in month one increasing to 8.44 in the month six clearly with a monthly total average of 7.441. This shows a significant difference in weight gain among the three age groups. The study found negative effects of time × age interaction on the children within 0-6 months in the first month up to the third month and in the last two months with 7-12 months. The effect was positive in the first two month with the age group 13-18.

On Gender, the average weight gain between male and female shows no significant difference during the study period (4.76 and 4.95 in the month one and 7.21 and 7.25 in month six). The growth was slightly higher among female children in the first three months and slightly lower than the male children in the last three months.

It can be concluded from the profile plot in figure 4.4 that the difference in weight gain between the two gender group were not significant suggesting that gender of a child does not really affect the weight gain of the child at the infant age. The difference was how ever among the three age groups, the feeding type and the feeding practices. This is shown in figures 4.1, 4.2, and 4.3.

The results reject the null hypothesis that the average weight gain is the same for the three age groups with the F ratio for the between subject (Age groups) equal 136.26 and the p- value of < .001 which is significant at 5% level. The hypothesis of Age by Time interaction was also rejected with the p-value of < .001 concluding that the effect of both time and age on weight gain was significant. The REML fixed model was

In table 4.5, the between subject (gender) effect was not significant. The F ratio for the gender was equal to 0.05 with the F probability of 0.825 far greater than 5% level of significance. Therefore we fail to reject the null hypotheses that gender does not influence growth in children at the infant stage. The sex of the child is insignificant as far as growth is concerned. Time was significant but the interaction between time and gender was not significant.

5.2 Recommendation

Base on the finding of the study, the following recommendations were made;

1. Nursing mothers should be encourage to frequently report at the weighing centers for the weight of their children to be taken as this will facilitate the early detection of malnutrition in children and other early childhood diseases.
2. The ministry of health should open weighing centers to solve the overcrowding situation in the metropolis since more nursing mother were reluctant to send their children for the monthly weighing because of the pressure at the centers.
3. The plumpy nut program initiated in the metropolis to improve nutritional status of the children less than five (5) years should be made to cover all children. This could be an incentive to mothers to always bring their children for weighing.
4. Educational programs on exclusive breast feeding during the first six months should be extended to cover all women especially the rural areas of the metropolis
5. Women should be encourage to see feeding their children themselves as paramount since feeding practice has a great influence in the growth of the children at the infant stages.

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APPENDIX A

Profile plot

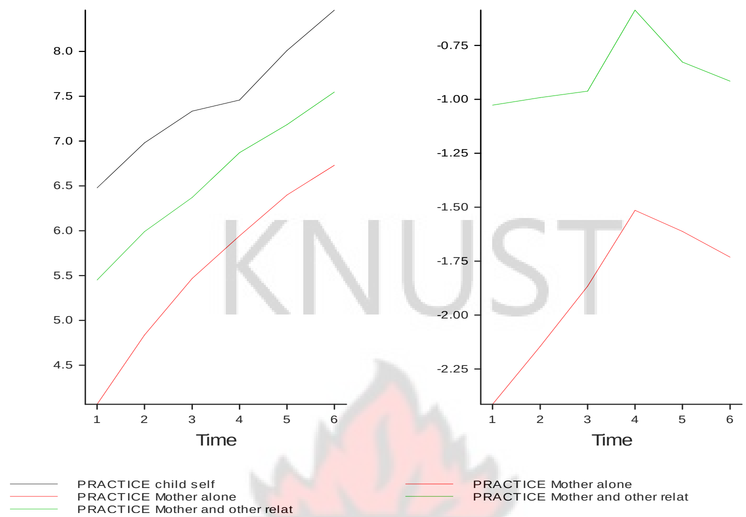


Figure 4.3 Mean Weight Gain for the Three Feeding Practices at Each Month

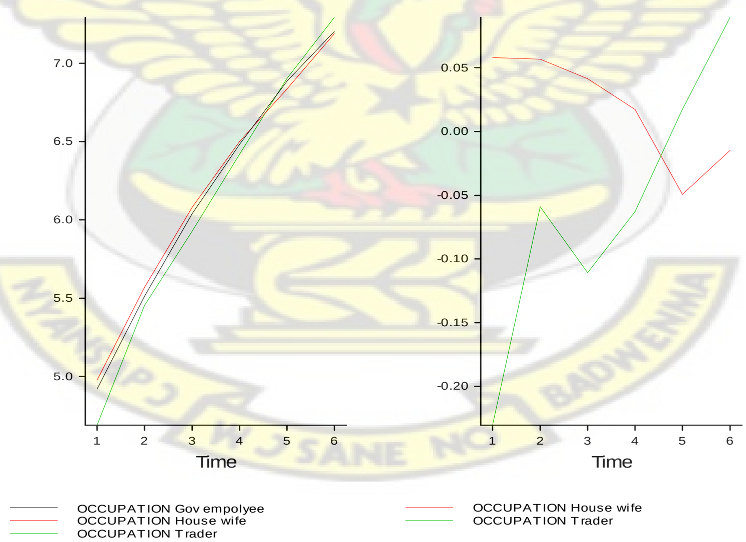


Figure 4.5 Mean Weight Gain for Mother's Occupation at Each Month

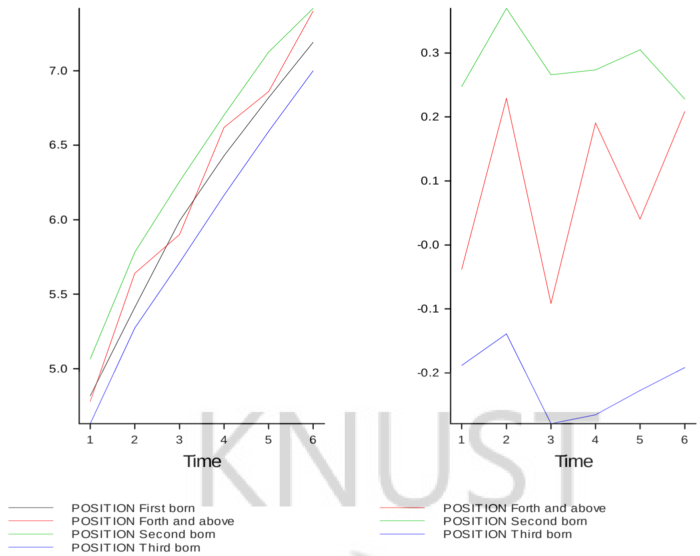
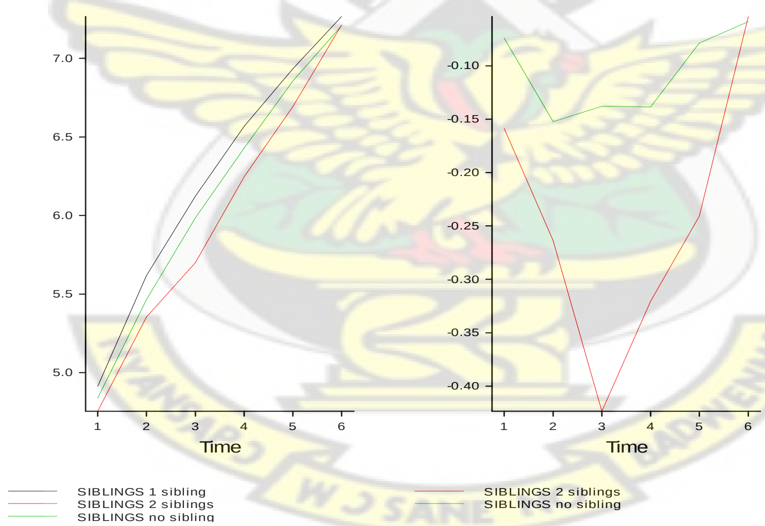


Figure 4.6 Mean Weight Gain for the Position of Birth at Each Month



Test of Hypotheses for Between Subject Effects					
Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
Subject stratum					
PRACTICE	2	512.2116	256.1058	24.00	<.001
Residual	207	2208.8354	10.6707	50.74	
UnivariateTest of Hypotheses for Within Subject Effects					
Subject.Time stratum					
d.f. correction factor 0.4649					
Time	5	814.9137	162.9827	775.01	<.001
Time.PRACTICE	10	18.4897	1.8490	8.79	<.001
Residual	1035	217.6583	0.2103		
Total	1259	3772.1087			
(d.f. are multiplied by the correction factors before calculating F probabilities)					

Table 4.12 Wald Tests for Gender Fixed Effects

Fixed term	Wald statistic	d.f.	Wald/d.f	.Chi-sqprob
Sequentially adding terms to fixed model				
Time	3611.27	5	722.25	<0.001
GENDER	0.05	1	0.05	0.824
Time._GENDER	6.48	5	1.30	0.262
Dropping individual terms from full fixed model				
Time._GENDER	6.48	5	1.30	0.262

Appendix B

DATA COLLECTED FOR THE ANALYSIS

S/No	**Age**	**Gen**	**Posit**	**sib**	**occu**	**feed**	**Pract**	**wt1**	**wt2**	**wt3**	**wt4**	**wt5**	**wt6**
1	1	2	1	1	3	1	1	3.0	4.0	4.5	4.4	4.5	5.0
2	1	2	1	1	3	1	1	3.2	4.5	5.6	6.6	6.7	6.9
3	1	1	4	3	2	1	1	2.8	5.3	6.0	7.0	6.9	7.5
4	1	2	3	3	3	1	1	4.8	5.5	6.0	6.2	6.6	6.7
5	1	2	2	2	3	1	1	3.3	3.7	4.4	4.9	5.6	6.1
6	1	1	2	1	3	1	1	3.5	4.3	5.0	5.7	6.1	5.4
7	1	1	1	1	3	1	1	3.7	3.7	4.7	5.1	5.7	6.0
8	1	1	3	2	2	1	1	3.0	5.8	6.2	6.7	7.0	7.4
9	1	1	3	2	2	1	1	2.7	3.5	5.4	6.5	7.4	7.5
10	1	2	1	1	3	1	1	3.5	4.0	4.8	5.5	6.1	6.7
11	1	1	3	3	2	1	1	3.2	3.9	4.0	5.1	5.9	6.3
12	1	1	1	1	3	1	1	3.4	4.9	6.0	6.5	6.9	7.2
13	1	1	2	2	1	1	1	3.7	4.3	4.9	6.1	6.6	7.3
14	1	2	1	1	3	1	1	3.9	4.7	5.5	5.7	6.2	6.6
15	1	2	2	2	3	1	1	3.3	4.3	4.9	5.5	5.8	6.1
16	1	1	1	1	1	1	1	3.0	3.5	3.6	4.1	4.8	4.7
17	1	1	1	1	2	1	1	2.6	2.9	3.4	3.4	3.6	3.9
18	1	2	3	2	2	1	1	3.4	5.4	6.0	6.6	7.1	7.6
19	1	2	1	1	1	1	1	3.8	4.2	4.8	5.5	5.8	6.1
20	1	2	3	2	3	1	1	3.3	3.8	4.0	4.7	5.5	6.0
21	1	2	3	2	3	1	1	3.0	3.2	3.6	4.2	4.5	4.4
22	1	1	1	1	2	1	1	3.3	4.1	4.8	5.4	5.6	6.2
23	1	2	2	1	2	1	1	3.0	3.9	4.5	5.4	6.0	6.4
24	1	1	3	2	1	1	1	3.4	3.8	4.4	4.9	5.3	5.6
25	1	1	1	1	3	1	1	2.5	3.3	3.6	3.9	4.4	4.5
26	1	2	2	1	3	1	1	2.9	3.6	3.8	4.4	5.0	6.2
27	1	1	3	2	1	1	1	2.7	3.5	4.1	4.4	4.9	5.0
28	1	1	3	2	3	1	1	2.6	3.6	4.1	4.5	5.2	6.0
29	1	2	3	2	1	1	1	3.2	3.8	3.9	4.6	5.0	5.2
30	1	1	3	2	1	1	1	2.8	3.5	3.8	4.2	4.9	5.4
31	1	2	2	1	2	1	1	3.2	4.0	4.4	4.9	5.6	6.2
32	1	2	2	1	2	1	1	3.5	4.0	4.2	4.6	5.0	5.2
33	1	2	2	1	1	1	1	3.8	3.9	3.8	4.1	4.3	4.8
34	1	1	3	2	2	1	1	2.4	3.4	3.7	4.3	5.1	5.3
35	1	1	1	1	3	1	1	2.0	2.6	3.2	3.7	4.4	4.8
36	1	2	1	1	3	1	1	2.9	3.3	4.0	4.2	4.4	4.9
37	1	2	1	1	3	1	1	3.5	3.8	4.0	4.4	4.9	4.8
38	1	2	3	2	3	1	1	3.0	3.7	4.4	4.9	5.5	5.4
39	1	1	2	1	2	1	1	3.1	4.0	4.5	5.1	5.7	6.0
40	1	2	3	2	1	1	1	2.7	2.9	3.6	3.8	3.8	4.5
41	1	2	1	1	3	1	1	3.2	3.8	4.1	5.2	6.6	7.2
42	1	2	1	1	1	1	1	3.5	4.3	6.8	6.8	7.1	7.4

43	1	2	3	2	1	1	1	3.8	3.7	4.2	4.4	4.7	5.8
44	1	1	2	1	1	1	1	1.2	3.2	4.1	4.5	5.0	4.8
45	1	2	1	1	3	1	1	3.5	5.7	6.4	6.7	6.9	7.0
46	1	2	2	2	1	1	1	2.7	4.1	5.0	5.5	5.8	6.0
47	1	2	1	1	2	1	1	2.9	3.5	4.0	5.3	6.4	6.7
48	1	1	1	1	1	1	1	3.0	3.6	4.9	5.1	5.6	5.8
49	1	2	2	2	1	1	1	2.9	3.4	4.4	5.5	6.0	6.5
50	1	1	3	2	1	1	1	3.2	4.9	5.8	6.7	6.9	7.3
51	1	1	1	1	2	1	1	3.0	3.8	4.7	5.4	6.4	7.0
52	1	1	2	2	3	1	1	3.1	3.8	4.7	5.3	5.6	6.4
53	1	2	1	1	3	1	1	2.8	3.5	4.3	4.8	5.1	5.4
54	1	2	1	1	2	1	1	3.0	3.6	3.7	4.5	4.9	5.2
55	1	1	1	1	1	1	1	3.5	4.0	5.2	5.8	6.0	6.6
56	1	1	2	2	2	1	1	2.4	3.9	5.3	5.9	6.4	6.5
57	1	1	2	2	3	1	1	3.0	3.8	4.2	5.7	6.1	6.0
58	1	2	2	2	2	1	1	3.4	3.9	4.7	4.8	5.6	6.1
59	1	1	1	1	2	1	1	2.4	3.0	3.6	3.9	4.4	4.7
60	1	1	3	2	2	1	1	2.9	3.4	4.1	4.8	4.9	6.4
61	1	1	1	1	2	1	1	2.3	3.2	4.2	5.3	6.2	7.1
62	1	1	1	1	2	1	1	2.4	3.0	3.4	3.7	4.2	4.6
63	1	2	3	1	2	1	1	3.3	4.6	5.5	6.0	7.0	8.1
64	1	2	3	2	2	1	1	2.4	3.5	4.0	4.6	5.0	5.4
65	1	1	2	2	2	1	1	3.8	4.2	4.8	5.4	6.0	6.8
66	1	1	1	1	2	1	1	3.5	4.0	5.5	6.8	7.7	8.4
67	1	1	1	1	2	1	1	3.2	4.0	4.4	6.3	7.1	7.4
68	1	1	2	1	2	1	1	3.0	3.5	3.7	4.2	4.7	5.0
69	1	2	1	1	1	1	1	2.2	3.4	4.6	4.6	5.4	6.0
70	1	2	2	1	2	1	1	2.8	4.6	5.6	6.1	6.6	6.9
71	2	2	2	2	1	2	2	5.0	6.2	6.0	6.2	6.5	6.7
72	2	1	3	3	1	2	2	4.4	5.1	5.5	6.0	6.2	5.8
73	3	1	2	2	1	2	2	6.0	6.3	5.9	6.8	7.3	7.2
74	2	1	3	2	2	2	1	5.5	6.2	6.5	6.5	6.6	7.0
75	2	2	3	2	1	2	1	6.5	6.8	7.2	7.4	7.6	7.7
76	2	2	2	1	1	2	2	4.5	5.0	5.3	5.8	6.0	6.5
77	2	1	2	1	2	2	2	5.6	6.2	6.2	7.4	7.5	7.9
78	2	2	1	1	3	2	1	5.5	5.5	6.2	6.4	6.3	6.7
79	2	1	1	1	1	2	2	6.5	7.0	7.5	7.8	7.5	7.5
80	2	2	1	1	1	2	2	6.0	6.6	7.0	7.3	7.5	8.4
81	2	1	2	1	3	2	1	4.3	5.1	5.7	5.9	6.5	6.4
82	2	2	1	1	1	2	2	3.5	5.2	6.8	7.0	7.5	7.8
83	2	1	3	3	1	2	2	3.3	3.9	4.8	5.4	6.8	7.7
84	2	2	1	1	2	2	1	5.0	5.9	6.2	6.6	6.9	7.1
85	2	2	3	2	1	2	2	4.8	5.5	5.7	6.1	6.5	6.3
86	2	1	3	2	2	2	2	4.3	5.1	5.7	6.1	6.3	6.5
87	2	2	3	3	1	2	2	4.8	5.1	5.6	6.0	6.4	6.9
88	2	2	4	3	1	2	2	5.7	6.0	6.2	6.5	6.9	7.2
89	2	1	1	1	2	2	2	5.6	6.2	6.6	7.0	7.4	7.2
90	2	2	1	1	1	2	2	5.5	6.1	6.6	7.0	7.3	7.5

91	2	2	2	2	3	2	1	5.5	7.3	7.9	8.4	8.6	8.0
92	2	1	3	2	1	2	2	4.6	5.3	5.7	5.8	5.8	6.2
93	2	2	1	1	2	2	1	4.8	5.3	5.7	6.8	6.5	7.0
94	2	1	3	2	2	2	1	5.5	6.2	6.5	6.5	6.6	7.0
95	2	2	3	2	1	2	1	6.5	6.8	7.2	7.4	7.6	7.7
96	2	2	2	1	1	2	2	4.5	5.0	5.3	5.8	6.0	6.5
97	2	1	2	1	2	2	2	5.6	6.2	6.2	7.4	7.5	7.9
98	2	2	1	1	3	2	1	5.5	5.5	6.2	6.4	6.3	6.7
99	2	1	1	1	1	2	2	6.5	7.0	7.5	7.8	7.5	7.5
100	2	2	1	1	1	2	2	6.0	6.6	7.0	7.3	7.5	8.4
101	2	1	2	1	3	2	1	4.3	5.1	5.7	5.9	6.5	6.4
102	2	2	1	1	1	2	2	5.0	5.2	6.8	7.0	7.5	7.8
103	2	1	3	3	1	2	2	3.9	4.6	4.8	5.4	6.8	7.7
104	2	2	1	1	2	2	1	5.0	5.9	6.2	6.6	6.9	7.1
105	2	2	3	2	1	2	2	4.8	5.5	5.7	6.1	6.5	6.3
106	2	2	3	3	1	2	2	4.8	5.1	5.6	6.0	6.4	6.9
107	2	1	2	2	1	2	2	4.0	4.8	5.8	6.3	6.6	6.7
108	2	1	1	1	2	2	2	4.3	5.5	5.0	5.5	5.6	5.8
109	2	2	1	1	2	2	2	3.9	4.2	5.5	6.3	6.4	6.9
110	2	2	4	3	1	2	2	3.4	4.7	5.2	5.5	5.0	5.9
111	2	1	3	2	1	2	2	4.6	5.3	5.7	5.8	5.8	6.2
112	2	2	1	1	1	2	1	3.6	4.3	5.4	5.9	6.5	6.9
113	2	2	2	2	3	2	2	5.0	6.2	6.6	7.2	7.8	8.0
114	2	2	1	1	3	2	2	6.5	6.0	6.5	7.2	7.4	7.9
115	2	1	1	1	3	2	2	7.5	7.9	7.5	7.7	7.9	7.5
116	2	2	2	1	3	2	2	4.8	5.2	5.8	6.0	7.0	7.2
117	2	2	2	1	2	2	2	5.0	5.4	5.5	6.4	6.7	7.2
118	2	2	2	2	1	2	2	4.8	5.0	5.5	6.2	6.5	6.4
119	2	1	2	2	1	2	2	4.5	5.6	5.9	6.4	6.9	6.7
120	2	2	2	2	1	2	2	4.9	5.0	5.2	6.2	6.5	7.0
121	2	2	1	1	2	2	2	4.8	5.0	5.7	6.2	6.0	6.3
122	2	2	1	1	2	2	2	4.6	5.6	6.3	6.6	7.1	7.4
123	2	1	2	2	1	2	2	3.9	5.5	6.3	6.7	7.1	7.7
124	2	1	1	1	2	2	2	4.2	5.2	6.0	6.3	6.7	7.0
125	2	1	1	1	1	2	1	5.0	6.4	6.9	6.5	7.0	7.3
126	2	1	3	2	1	2	2	6.0	7.0	7.0	7.0	7.5	7.8
127	2	1	3	2	1	2	1	5.9	6.3	7.5	7.9	8.0	9.0
128	2	1	3	3	2	2	1	5.7	5.9	6.0	6.0	6.0	6.4
129	2	2	4	3	2	2	2	6.5	6.5	7.0	7.1	7.5	7.8
130	2	1	2	1	2	2	2	4.1	6.5	6.8	7.0	7.3	8.0
131	2	1	2	1	2	2	2	4.7	5.5	5.5	6.0	7.0	7.5
132	2	1	2	2	3	2	2	3.8	4.6	4.9	6.0	5.8	6.3
133	2	2	2	2	3	2	1	8.0	9.2	9.4	9.8	9.9	9.6
134	2	1	1	1	1	2	1	5.2	5.8	6.2	6.6	7.2	6.7
135	2	1	2	2	3	2	1	4.9	6.5	6.9	7.0	7.3	8.0
136	2	1	1	1	2	2	2	7.6	7.9	7.5	7.9	8.5	8.0
137	2	1	1	1	3	2	2	5.0	5.5	6.0	7.5	5.0	6.5
138	2	1	1	1	2	2	2	3.5	5.0	5.5	5.5	6.4	7.0

139	2	2	1	2	3	2	1	4.2	5.5	6.0	6.5	7.1	7.8
140	2	1	3	2	3	2	1	6.2	6.5	7.0	7.5	7.5	7.8
141	3	1	3	2	2	3	1	5.9	7.0	7.7	7.9	8.0	8.0
142	3	2	1	1	1	3	2	4.2	4.6	4.7	5.3	5.3	5.0
143	3	1	2	1	2	3	2	5.7	6.5	7.2	7.6	7.5	7.9
144	3	1	2	1	1	3	2	5.3	5.7	6.4	6.3	6.5	6.0
145	3	1	4	3	1	3	2	5.5	5.7	5.1	7.0	8.0	8.6
146	3	2	1	2	2	3	2	6.0	6.5	6.8	7.0	7.2	7.2
147	3	1	2	1	3	3	2	5.9	6.5	7.0	7.5	8.0	8.9
148	3	1	1	1	3	3	2	5.5	6.2	6.0	7.0	7.5	8.0
149	3	1	1	1	3	3	2	5.8	6.0	6.3	7.5	8.0	9.5
150	3	2	1	1	1	3	3	8.0	8.5	8.0	8.7	8.7	9.0
151	3	2	1	1	2	3	2	5.7	6.5	6.5	7.5	8.0	8.8
152	3	2	1	2	1	3	3	6.4	4.5	5.0	5.5	5.5	6.0
153	3	2	1	1	1	3	3	4.0	4.4	5.0	5.5	6.5	7.0
154	3	1	2	2	2	3	3	6.0	6.8	7.2	7.7	8.6	8.0
155	3	1	2	2	2	3	2	7.0	7.9	9.3	9.3	9.5	9.8
156	3	2	2	2	1	3	2	6.0	6.6	7.0	7.5	7.6	8.3
157	3	2	2	2	2	3	2	8.2	8.5	8.5	9.0	9.2	9.6
158	3	1	2	1	2	3	2	4.5	5.5	5.8	6.0	6.5	7.3
159	3	1	3	1	2	3	2	6.5	6.5	7.0	7.5	7.9	8.2
160	3	2	2	1	1	3	2	7.4	7.9	7.8	7.2	8.0	7.9
161	3	2	3	1	2	3	2	4.5	5.6	6.0	6.5	6.0	6.3
162	3	2	3	1	2	3	3	6.5	6.8	6.5	6.3	7.5	7.8
163	3	1	2	2	2	3	3	5.8	6.8	7.0	7.5	7.5	8.0
164	3	1	2	2	1	3	2	6.0	6.4	6.0	7.0	7.5	7.0
165	3	2	3	2	1	3	2	5.5	5.8	5.5	6.5	6.0	6.3
166	3	2	2	2	1	3	2	5.0	4.5	5.5	5.6	5.6	6.5
167	3	1	2	2	1	3	3	7.2	8.5	9.0	8.5	9.5	9.5
168	3	2	1	1	1	3	2	5.5	5.6	5.8	6.3	7.0	7.4
169	3	1	1	1	2	3	3	4.6	5.3	5.8	5.2	6.0	6.4
170	3	1	2	2	2	3	3	6.5	6.5	7.1	7.3	8.6	8.0
171	3	2	1	1	2	3	3	5.1	6.0	6.3	6.0	7.9	8.0
172	3	2	1	1	1	3	2	5.5	5.8	6.0	6.9	6.9	8.0
173	3	2	1	1	1	3	2	9.2	9.8	10.0	10.8	11.0	11.0
174	3	2	2	1	1	3	1	4.2	5.3	6.0	7.1	7.6	8.0
175	3	1	1	1	1	3	1	5.0	5.9	6.8	7.0	7.6	7.6
176	3	1	1	1	1	3	2	5.1	5.4	6.0	6.5	7.0	7.3
177	3	2	1	1	1	3	3	6.0	7.3	8.5	8.9	9.4	10.0
178	3	2	1	1	1	3	3	6.9	7.0	7.5	7.6	7.5	8.5
179	3	2	1	1	1	3	3	7.0	7.0	7.5	7.2	7.1	8.3
180	3	1	2	2	1	3	3	6.5	7.5	8.0	8.5	8.0	9.0
181	3	2	2	2	2	3	1	4.7	5.4	6.6	5.9	7.5	7.3
182	3	1	2	2	1	3	2	5.6	5.5	6.3	7.0	7.2	7.8
183	3	2	2	1	2	3	2	5.5	5.8	6.0	6.5	7.0	7.7
184	3	1	2	1	3	3	2	7.8	6.9	6.8	6.9	6.5	6.8
185	3	2	2	1	3	3	2	5.3	5.2	6.0	6.5	7.3	7.9
186	3	1	3	3	3	3	1	7.0	7.0	7.5	8.0	8.5	9.3

187	3	2	3	3	2	3	2	5.5	6.0	6.2	6.5	6.5	7.5
188	3	1	2	2	3	3	2	8.0	8.4	9.8	10.2	10.8	11.3
189	3	2	3	1	2	3	2	5.6	5.3	5.5	7.3	8.0	8.9
190	3	2	2	2	3	3	3	6.0	7.4	7.5	7.5	7.3	8.5
191	3	2	3	2	3	3	3	9.0	9.3	9.0	9.0	10.2	11.0
192	3	2	2	2	3	3	1	8.4	8.6	9.0	9.1	9.7	9.4
193	3	1	3	1	3	3	1	7.0	7.5	8.2	8.7	9.9	9.0
194	3	1	2	1	3	3	1	6.7	7.0	7.0	7.1	7.0	7.5
195	3	2	1	1	2	3	1	7.5	8.3	8.8	9.5	10.0	11.0
196	3	1	1	1	2	3	3	7.2	7.9	8.0	8.0	8.6	9.0
197	3	2	1	1	2	3	1	9.0	9.8	10.0	10.0	10.7	11.0
198	3	1	1	1	2	3	3	7.8	7.9	8.6	8.5	9.0	9.7
199	3	1	3	1	1	3	3	6.1	6.7	7.0	7.3	7.8	8.7
200	3	1	1	1	1	3	3	5.0	5.8	6.5	6.9	7.5	7.5
201	3	2	2	2	1	3	3	8.4	8.7	9.0	9.0	9.5	9.8
202	3	1	2	2	1	3	1	7.1	7.9	8.0	8.7	8.0	9.2
203	3	2	2	1	1	3	1	7.5	8.3	9.5	9.6	10.3	9.9
204	3	1	2	1	1	3	1	8.0	8.8	8.9	9.0	9.5	9.9
205	3	2	1	1	3	3	1	11.0	10.0	11.5	10.6	11.4	11.0
206	3	2	2	2	3	3	2	7.8	8.4	9.3	9.0	9.9	10.4
207	3	1	1	1	2	3	2	8.0	8.2	8.8	9.0	9.5	10.0
208	3	1	1	1	2	3	2	5.1	5.8	6.0	6.5	7.0	7.0
209	3	1	2	1	3	3	2	6.5	6.5	7.1	7.3	8.6	8.0
210	3	1	3	2	2	3	2	8.5	8.5	9.0	9.7	10.2	10.8

Appendix C


12/07/2010


12/14/2010