KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY, KUMASI, GHANA

INSTITUTE OF DISTANCE LEARNING

SCHOOL OF PHYSICAL SCIENCES

DEPARTMENT OF MATHEMATICS

ASSESSING THE EFFECT OF VACCINATION ON CHILD MORTALITY IN RURAL SOUTHERN GHANA

by

JONAS KOFI AKPAKLI

BA. Computer Science and Statistics (Hons.)

May, 2012

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A Thesis Submitted to the Department of Mathematics, Kwame Nkrumah University of Science and Technology, Kumasi, in partial fulfillment of the requirement for the degree of Master of Science in Industrial Mathematics, Institute of Distance Learning.

by

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BA. Computer Science and Statistics (Hons.)

May, 2012

CERTIFICATION

I herein certify that, this work was carried out solely by Jonas Kofi Akpakli (PG 4062010) in the department of Mathematics, Institute of Distance Learning, in partial fulfilment of the requirement for the award of Master of Science Degree in Industrial Mathematics.

Dr. Samuel Kwame Amponsah ....

Supervisor's Name Signature Date

DECLARATION

I hereby declare that this submission is my own work towards the Master of Science degree and that, to the best of my knowledge it contains no material previously published by another person nor material which has been accepted for award of any other degree of the university except where due acknowledgement has been made in the text.

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Certified by:

Mr. K. F. Darkwah	.....	.....
Head of Mathematics Department's Name	Signature	Date

DEDICATION

I dedicate this project to God Almighty for his guidance, protection and direction, to my beloved parents (Mr. S.G.K Akpakli and Madam E.C Hatsu), Mr. A. Hatsu, the late uncle, Mr. A.Y Akpakli, who laid the solid foundation for my informal and formal education and my siblings, for their prayers and encouragements during my course of studies.

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List of Abbreviations

BCG	Bacillus Calmette-Guérin
CHPS	Community Based Health Planning and Services
DHDSS	Dodowa Health and Demographic Surveillance System
DHIS	District Health Insurance Scheme
DHMT	District Health Management Team
DHRC	Dodowa Health Research Centre
DHS	Demographic and Health Survey
DQA	Data Quality Audit
DTP	Diphtheria-Tetanus-Pertussis
EPI	Expanded Programme on Immunisation
GACVS	Global Advisory Committee on Vaccine Safety
GAVI	Global Alliance on Vaccines and Immunisation
GDHS	Ghana Demographic and Health Survey
GHS	Ghana Health Service
GIS	Geographic Information System
GSS	Ghana Statistical Service

HDSS	Health and Demographic Surveillance System
HRS	Household Registration System
ISS	Immunisation Services Support
KNBS	Kenya National Bureau of Statistics
MCV	Measles Containing Vaccines
MDGs	Millennium Development Goals
NIDs	National Immunization Days
TBA	Traditional Birth Attendant
UCI	Universal Childhood Immunisation
UN	United Nations
UNFPA	United Nations Population Fund
UNICEF	United Nations Children's Fund
WHO	World Health Organization
YF	Yellow Fever

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ABSTRACT

Research in northern Ghana has shown that vaccination indeed reduces childhood mortality (Nyarko et al., 2001). This dissertation seeks to assess the vaccination status of children aged 12 to 71 months at death and that of children who are alive and the effect of incomplete/partial vaccination on mortality in Dangme West District of Ghana. The data are from the death registration and vaccination status forms. Death registration forms are updated bi-annual and vaccination status are updated yearly for children two(2) years and below at the Dodowa HDSS site. Descriptive statistics was used to study the progress of vaccination status of children born from 2005 to 2009. Bivariate analysis was employed to ascertain difference between vaccination status of children who were dead and that of those who are alive. Multivariate logistic regression analysis was also used to investigate immunisation as a predictor of child mortality after controlling for sex and age of a child and household wealth index. Fully immunised is defined by GSS et al., 2009 as a child who received a BCG, measles and three doses each of DPT and Polio vaccines (excluding polio vaccine given at birth). Partially Immunized is a child who did not receive all the 8 basic vaccines. Included in this analysis were only children whose vaccination cards were seen by the data collectors. The analysis revealed that about half (54.8%) of children aged 12 -71 months who died were fully immunised compared to 67.8% of children aged 12-71 months who were alive. Children who were partially immunised were 1.7 times more likely to die compared to those who were fully immunised (OR=1.73, 95% CI: 1.15, 2.61). The likelihood of partially immunised child dying was 1.1 times, after controlling for child's gender and age and household wealth index (quintiles) (OR=1.12, 95% CI: 0.71, 1.77). To achieve MDGs goal 4 there is a need for intense public education or house to house education by the policy makers and programme planners on the need for people to complete their vaccination.

CHAPTER ONE

1.0 INTRODUCTION

Childhood immunization is very important in preventing health related diseases and childhood death. Immunization during childhood has been proven to be the most effective strategy for the prevention of many infectious diseases (Anderson, 1992). World Health Organization (WHO) estimates that more than two million five hundred thousand (2.5 million) deaths among all age groups worldwide are averted annually by immunization against diphtheria, tetanus, pertussis, and measles (WHO et al., 2008). Recent estimates indicates that the global Diphtheria-Tetanus-Pertussis three (DTP3) immunization coverage of infants is 82%, and twenty three million five hundred thousand (23.5 million) children did not receive DTP3 vaccine in 2008 (WHO et al., 2008). Although the recent trend related to global vaccination coverage is positive with One hundred and twenty two (122) countries reaching 90% DTP3 coverage in 2009, pockets of undervaccination continue to persist in parts of sub-Saharan Africa (WHO, 2009).

In response to the worldwide call to improve child survival, the Expanded Programme on Immunization (EPI) advocated by UNICEF was wholly embraced by Ghana in the early 1980s. As in most developing countries, immunization against the six immunizable childhood diseases (i.e., diphtheria, measles, pertussis, poliomyelitis, tetanus, and tuberculosis) has been instituted as part of Ghana's primary health care program. Access to the antigens is mainly through outreach programs, particularly in remote areas, and through routine child clinic sessions at health care facilities. While the EPI in Ghana in the early 1980s was described as a great success, falling coverage rates characterized the period 1986–91 (UNICEF, 1993). In the past twenty years, the percentage of children age 12-23 months who have been fully immunized has

increased from 47 percent in 1988 to 79% in 2008 (GSS et al., 2009). However, this proportion varies from 58.5% in Northern Region to 93.9% in Brong Ahafo Region. Fully immunized children in Greater Accra region is 79.9%. Despite this improvement, the worldwide target of 90 percent coverage by the year 2015 is far from being attained. Boys and rural children (80% and 79%, respectively) are slightly more likely to be fully vaccinated compared with girls and urban children (78% each) (GSS et al., 2009).

The lack of reliable data on EPI-targeted diseases as causes of death makes it difficult to assess the magnitude of mortality reductions due to immunization uptake. It has been argued that reductions in disease-specific mortality will not necessarily translate into improvements in child survival in situations where children are at high risk of death from other causes. This argument holds that those "saved" by immunization may be weaker, on average, than those who would have survived without immunization, and therefore more likely to die of other causes (Koenig et al., 1991; Mosle et al., 1984; Kasongo Project Team, 1981). Others have argued against this view, claiming that immunization prevents not only death but also illness, thereby promoting the overall health of the child and reducing mortality by more than the share of deaths directly attributable to the targeted diseases (Kristensen et al., 2000; Aaby, 1995; Koenig et al., 1991).

1.1 BACKGROUND OF STUDY

Childhood vaccination reduces child mortality significantly and is a cost effective way to improve child health, particularly for poor households located in high-disease environments (Koenig et al., 2001; Breiman et al., 2004; Brenzel et al., 2006). Vaccination of children is thought as an investment in human capital, with children's health improvements resulting in their

higher worker productivity and earnings as adults. The argument for viewing health interventions as techniques for promoting economic success and poverty reduction was set out in the report of the Commission on Macroeconomics and Health WHO, 2001. (Bloom et al., 2005) use estimates of the effect of vaccination on mortality rates, combined with estimates of the effect of life expectancy on productivity, to estimate that full immunization with six standard vaccines has a rate of return around 18% (about the same rate as primary education) as an investment in human capital, despite the long delay between childhood vaccination and entering work.

In Kenya, the proportion of children aged 12-23 months that are reported to have received all recommended vaccinations is 77.4% (KNBS et al., 2009). However, this proportion varies from 48.3% in the North Eastern Province to 85.8% in the Central Province. This geographical inequality in coverage reflects the variation in the influence of determinants of full vaccination across the different provinces. In Nairobi, 73% of children in this age range are reported to have received all vaccinations (KNBS et al., 2009). Studies carried out in the Mathare slum of Nairobi have shown that parental age, marital status, level of education and poor knowledge about vaccinations are significantly associated with completion of the immunization schedule by under-5 children (Kamau et al., 2001). Other factors identified as predictors of incomplete vaccination among socio-economically disadvantaged children in the United States include lack of family support, lack of adequate prenatal care use, financial barriers and single motherhood (Bates et al., 1994; Bates et al., 1998).

A study conducted in northern part of Ghana indicates that coverage by one Bacillus Calmette-Guérin (BCG) shot, three sets of polio drops, and three DPT shots reduces mortality between

ages 4 and 8 months by nearly 90%. Complete coverage by all EPI antigens reduces mortality between ages 9 and 59 months by 70%. BCG, polio, and DPT vaccines without measles vaccination reduce mortality by 40 percent. The independent reduction in mortality associated with measles vaccination is 50% (Nyarko et al., 2001). Despite recent improvements in child survival in Ghana, mortality levels are still very high. The estimated national infant mortality rate is 57 per 1,000 live births while under-5 mortality is 108 per 1,000 live births (GSS et al., 1999). In rural settings where health services are not accessible to a large proportion of the population, the situation is even worse.

Further, immunization drives could affect mortality through behavioral as well as biomedical pathways. Health workers generally use designated national immunization days (NIDs) to measure and weigh children and provide a wide range of health-related information. NIDs serve as a contact point with the official health care system for mothers, especially in rural areas, who might otherwise rarely interact with the system.

However, logistical difficulties, particularly in settings such as rural southern Ghana, may limit an immunization program's potential for impact. In most rural areas, the schedules for EPI outreach may not correspond to the exact time at which a child is due for a particular antigen. For maximum protection against the six childhood killer diseases, it is recommended that a child receive one dose of Bacillus Calmette-Guérin (BCG) at birth; three doses of diphtheria, pertussis, and tetanus (DPT) vaccine and polio drops at ages 6, 10, and 14 weeks; and the measles vaccine at age 9 months. Outreach programs are usually planned to correspond to days of local activity

(such as market days, non-farming/non-fishing days, and so forth) and at reasonable intervals to ensure adequate response to the call to send children to outreach points. Complete uptake may, therefore, not necessarily result in improvements in child survival because vaccinations may be mistimed. In other situations, mothers may fail to return for later vaccines. This is particularly true for the measles vaccine, which should be given nearly six months after completion of the rest of the series. Thus, the full benefit of the immunization routine for the child may not be achieved. In addition, vaccines may lose their sensitivity during transportation between a health institution and an outreach point because of unsatisfactory storage facilities. Most vaccines need to be stored at low temperatures to maintain their potency. In cases where the cold chain is broken due to unavailability of refrigeration facilities, the antigen may have lost its effectiveness by the time it is administered to a child. This problem of transporting vaccines under unsatisfactory conditions is often encountered in rural areas.

In Dangme West District, however, efforts are made to maintain the cold chain by providing vaccines to nurses just before they begin their outreach duties. Nevertheless, considering that the climate in the district is very hot, even an hour's drive to an outreach point can break the cold chain. The aim of this study is to assess the effect of incomplete immunization of children aged 12 to 71 months using logistic regression in Dangme West District of Southern Ghana.

1.2 THE STATEMENT OF THE PROBLEM

Study conducted in sub-Sahara Africa reveals that childhood vaccination indeed reduces child mortality. National EPI Policy is that each child should receive one dose of BCG at birth, three doses of DPT, (at 6, 10 and 14 weeks), four doses of OPV (at birth, 6, 10 and 14 weeks), one

dose of measles (at 9 months) and one dose of yellow fever (at 9 months), Ghana replaced DPT in the scheme with the pentavalent vaccine (DPT-Hib-HeB). EPI coverage focuses on the total number of people that they have vaccinated divided by the projected number of people. Research conducted by GSS et al., over the years focus on the vaccination status of surviving children. Childhood vaccination is very important and there has being lot of research with respect to vaccination coverage. Most of these researches focus on the vaccination of children that are alive without considering the vaccination status of children who had died. As such, there is a need to know the vaccination coverage of children who have died.

1.3 OBJECTIVES

The objectives of the study are:

(i) to assess the effect of incomplete/partial immunisation of children aged 24 to 71 months on mortality using logistic regression

(ii) to compare the vaccination coverage for both surviving and dead children, and

(iii) to make recommendations to policy makers, stakeholders and the general public.

1.4 SIGNIFICANCE OF THE STUDY

Immunization during childhood has been proven to be the most effective strategy for the prevention of many infectious diseases (Anderson, 1992). Others have argued against this view, claiming that immunization prevents not only death but also illness, thereby promoting the overall health of the child and reducing mortality by more than the share of deaths directly attributable to the targeted diseases (Kristensen et al., 2000; Aaby, 1995; Koenig et al., 1991).

The findings of this study would help the policy planners, individuals and households to appreciate the long term devastating effects of the vaccination on human, community and national development.

This work is worth doing because this study will help us compare the vaccination coverage of children who were dead and children who are alive and in order to assess the effect of incomplete vaccination of children aged 12 to 71 months using logistic regression

Furthermore, the solution of this problem can help policy makers to develop comprehensive policies tailored to the needs of the economies of individual households, and the nation as a whole.

Moreover, the solution of this problem would help policy makers and the governments to come out with strategies to ensure that children are immunized in order to meet our universal coverage.

1.5 METHODOLOGY

Secondary data on vaccination, deaths and household's socioeconomic status were obtained from Dodowa Health Demographic Surveillance System (DHDSS) site between 2005 and 2011 data collection periods. Descriptive statistics will be used to study the progress of vaccination status of children (alive or were dead) born from 2005 to 2009. Bivariate analysis will be used to compare vaccination coverage and child survival. Chi-square test or Fisher's exact test will be used to test the differences in the vaccination of surviving and death children. Logistic Regression will be used to investigate the association between the vaccination status and

mortality. Fully vaccinated is defined by GDHS 2008 as a child who received a BCG, measles and three doses each of DPT (Pentavalent) and Polio vaccines (excluding polio vaccine given at birth). Included in this analysis were only children whose vaccination cards were seen by the data collectors. The data will be analysed using STATA and SPSSS.

1.6 RESEARCH LIMITATIONS

This study excludes all children who:

(i) have move out of the district before 31st of December 2010

(ii) received vaccination and health card not available

(iii) never received any vaccination

(iv) aged under 12 months and above 71 months

1.8 ORGANIZATION OF THE STUDY

This study consists of five chapters. Chapter one of the study is the introduction, the background of the study, statement of the research problem, objectives of the study, methodology, significance of the study, research limitations and organisation of the study. In chapter two, we shall put forward related literature in the field vaccination. Chapter three presents the methodology employed in carrying out the study which includes: study area, study sample and design, data storage and analysis, measures, concept of logistic regression and ethical considerations. Chapter four is devoted for data collection and analysis. Finally, chapter five presents the summary of the research findings, conclusions and recommendations of the study.

CHAPTER TWO

2.1 IMMUNISATION

In many countries, vaccine-preventable diseases remain major causes of child mortality (Lopez et al., 2006). Delivery of childhood immunisations is an essential dimension of health systems and is included as an indicator for Millennium Development Goal 4. Overall performance of immunisation programmes has most often been tracked with the coverage of three doses of diphtheria, tetanus, and pertussis vaccine (DTP3).

Over the past 30 years, substantial resources have been invested through global initiatives to scale up immunisation coverage (Hardon et al., 2005; Jolly, 2004). In 1974, WHO launched the Expanded Programme on Immunisation (EPI). After this programme, in 1977, a global goal for universal child immunisation against the six basic antigens (measles, poliomyelitis, diphtheria, pertussis, tetanus, and tuberculosis) was articulated at the World Health Assembly (Keja et al., 1988).

In 1984, UNICEF in partnership with others launched the Universal Childhood Immunisation (UCI) by 1990 initiative, defined as 80% immunisation coverage (Hardon et al., 2005). UCI mobilised substantial funds and support for delivery of immunisation services and, in 1990, UNICEF declared that UCI's target had been achieved (Cutts, 2000).

In the 1990s, estimates suggested that improvements in immunisation coverage were stagnating or falling (Hardon et al., 2005; Brugha et al., 2002; Starling et al., 2002).

In response, the Global Alliance on Vaccines and Immunisations (GAVI), a public–private partnership that aims to increase coverage of basic vaccines and to accelerate the introduction of new vaccines in low-income and middle-income countries, was launched in 1999.

Although GAVI provides a range of support, Immunisation Services Support (ISS) is the funding that aims to increase coverage of basic vaccines such as DTP3. ISS is provided in response to country proposals and represents flexible cash that countries can use to improve immunisation performance (GAVI, 2008). ISS payments are performance-based, with funds disbursed in proportion to the number of additional children less than one(1) year of age targeted or reported to receive DTP3. Payments are divided between two phases: an investment phase (the first two (2) years after a country's proposal has been approved) and a reward phase (the third year and onwards after approval) (GAVI, 2008). During the investment phase, US$20 is disbursed per additional child targeted by the country to receive DTP3 in the first year following approval of GAVI support. The baseline for determination of the additional number is the number of children receiving DTP3 in the year before the approval of ISS. In the reward phase, GAVI disburses US$20 per additional child reported by countries to receive DTP3, compared with the target set during the investment phase or the number of children receiving DTP3 in the previous year if this number is higher.

The number of additional children receiving DTP3 is based on official reports from countries to WHO and UNICEF. These reports are largely but not exclusively based on administrative data from health-service-provider registries. In recognition of the weakness of administrative data systems and the potential for ISS to induce incentives for over reporting, GAVI requires

countries to pass a Data Quality Audit (DQA) of their administrative data system to be eligible for reward payments (Ronveaux et al., 2005; GAVI, 2008).

Data Quality Audits (DQAs) are used to assess the accuracy of reports from health centres to districts and nationally on the number of additional children immunised with DTP3 by comparing this number against a re-count of paper records in health centres (Ronveaux et al., 2005). Sample surveys are the other main source of data on immunisation coverage. These include standardised multicountry surveys, such as the Demographic and Health Surveys (DHS), as well as country-specific surveys, such as the EPI 30-cluster by seven household surveys. Using both officially reported data and survey data, WHO and UNICEF jointly publish estimates of national and global DTP3 immunisation coverage (WHO et al., 2008).

WHO and UNICEF estimates aim to reconcile differences between reported and survey data; however, their estimation is not undertaken in a reproducible way and nor do they include an estimation of uncertainty for the measurement of coverage. There are several lingering concerns about the measurement of coverage. The quality of administrative data on immunisation coverage remains suspect due to problems with measurement (Murray et al., 2003) as well as the potential for target-oriented initiatives such as UCI (Hardon et al., 2005; Mavimbe et al., 2005; Onta et al., 1998) and performance-based payment systems such as GAVI's ISS (Hardon et al., 2005; Starling et al., 2002) to encourage health-service providers to over-report coverage. A previous analysis (Lu et al., 2006) did not detect an effect of GAVI ISS on over-reporting, measured as the difference between officially reported and survey-based coverage; however, new data are now available to assess this effect in a larger number of countries.

There is now clear evidence that the simplistic conventional model of immunization is invalid (Shann, 2010). We can no longer assume that a vaccine acts independently of other vaccines, or that it influences only infections caused by the target disease. Strong evidence from randomized trials suggests that Bacillus Calmette-Gue´rin vaccine (BCG) reduces mortality from infections other than tuberculosis and that measles vaccine reduces mortality from infections other than measles (Shann, 2010; Roth et al., 2006; Roth et al., 2010; Aaby et al., 2011).

However, there is worrying evidence that whole cell diphtheria-tetanus-pertussis vaccine (DTP) may increase mortality from infections other than diphtheria, tetanus, or pertussis in high-mortality areas (Shann, 2010; Roth et al., 2010; Aaby et al., 2011; Aaby et al., 2007; Aaby et al., 2004; Aaby et al., 2004). These nonspecific effects of BCG, measles vaccine, and DTP are generally stronger in girls, appear to be maximal in the first 6 months after immunization, and are largely determined by the most recent vaccine administered (Shann, 2010). Randomized trials show that measles vaccine has strong nonspecific effects. Providing it is not given after vitamin A or followed by DTP, measles vaccine reduces mortality from diseases other than measles by 45% (95% confidence interval [CI], 14%–65%) when given at 4.5 months of age, and by 47% (95% CI, 23%–63%) when given to girls at 9 to 10 months of age (Shann et al., 2010).

Study from Guinea-Bissau shows that BCG has potent nonspecific effects on mortality (Aaby et al., 2011). Low-birth-weight neonates were randomized to receive BCG at birth or via the routine immunization program at an older age (median, 7.7 weeks). The biological effects of BCG are shown by the outcome during the first 4 weeks after randomization, before children in either group had been given DTP and when few children in the control group had received BCG. In this

period, BCG reduced mortality by 45% (95% CI,11%–66%); there were fewer deaths from sepsis and acute respiratory infection, and no deaths from tuberculosis (which is a rare cause of death at this age). This spectacular reduction in mortality is consistent with the results of 6 controlled trials performed in 45,662 children in the United States and the United Kingdom in the 1940s and 1950s, in which BCG reduced mortality from causes other than tuberculosis by 25% (95% CI, 6%–41%) (Shann, 2010; Roth et al., 2006).

Although BCG reduced mortality in the first 4 weeks of life in the trial in Guinea-Bissau, investigators observed no difference in mortality after that age (Aaby et al., 2011). This is not surprising, because by 2 months of age 58% of the controls had received BCG and over 60% of children in both groups had received DTP. Consequently, BCG did not significantly reduce mortality in the first 12 months of life, the observed reduction being 17% (95% CI, 28% to 37%). This was the primary endpoint of the trial, which was underpowered because infant mortality was 101 deaths per 1000 live births, rather than 250 deaths per 1000 live births as predicted when the trial was designed. A lower than-expected mortality often occurs when trial participants in a high mortality area are offered free treatment, as in this study. This illustrates how difficult it is to do randomized trials in high-mortality areas, where we most need to obtain information about how to lower mortality. A worrying finding in this trial was that children who had received DTP by 2 months of age had an increased mortality between 2 and 6 months of age: Mortality was increased 4.3-fold (95% CI, 1.5–12.2-fold) in the BCG at-birth group and 1.7-fold (95% CI, .7– 4.0-fold) in the control group (Aaby et al., 2011). DTP was observed to have similar effects in a randomized trial of revaccination with BCG at 19 months of age in Guinea-Bissau (Roth et al., 2010). In that trial, 60% of the participants had not received their last dose of DTP (DTP4) at

the time of enrollment, and many of these children were given DTP4 after entering the study. Children who received BCG had a lower mortality than controls if they had received DTP4 before enrollment (hazard ratio, .36; 95% CI, 0.13–0.99) but a higher mortality if they had not received DTP4 before enrollment (hazard ratio, 1.78; 95% CI, 1.04–3.04); the difference was highly significant (P=0.006). Mortality was 0.36 deaths per 100 person-years if DTP4 had been given before BCG revaccination, 1.02 deaths per 100 person-years in controls who were not revaccinated with BCG (mortality was not affected by DTP4 status at enrollment), and 1.83 deaths per 100 person-years if DTP4 had not been given before BCG revaccination (Roth et al., 2010; Shann, 2010). These two(2) studies suggest that BCG lowers mortality if it is given alone or after DTP, but that mortality may be increased if DTP is given after BCG as recommended in the schedule for the Expanded Program on Immunization (EPI) (Roth et al., 2010; Aaby et al., 2011). The administration of DTP after BCG was not randomized in these studies, so the observed increase in mortality with DTP may have been caused by bias.

However, this seems unlikely. In the trial of BCG in low-birth-weight babies (Aaby et al., 2011), the infants who had received DTP by 2 months of age (and had increased mortality) were larger babies who would be expected to have a lower mortality in the absence of a nonspecific effect of DTP. In the trial of BCG revaccination at 19 months of age (Roth et al., 2010), mortality in the control group (no additional BCG) was not influenced by DTP4 status at the time of randomization, suggesting that this was not an independent risk factor. Even in unimmunized communities, diphtheria, tetanus, and pertussis cause far fewer deaths than pneumonia, sepsis, and diarrhea (Preston,1976); despite reducing mortality from diphtheria, tetanus, and pertussis, DTP will, therefore, increase total mortality if it causes even a small increase in mortality from

pneumonia, sepsis, and diarrhea in high-mortality areas (Shann, 2010). When DTP was first introduced into Guinea-Bissau, despite the absence of herd immunity, mortality was 5.1 deaths per 100 person-years among children who did not receive DTP but 11.3 deaths per 100 person-years among children who did receive DTP (risk ratio, 2.03; 95% CI, 1.17–3.52) .

No randomized trial has demonstrated that it is safe to give DTP to young infants in high-mortality areas, and there is now worrying evidence that DTP may increase mortality under these circumstances—especially when it is given after BCG as recommended in the EPI schedule (Shann, 2010; Roth et al., 2010; Aaby et al., 2011; Aaby et al., 2007; Aaby et al., 2003; Aaby et al., 2004). In 2002, 2003, and 2004, the WHO Global Advisory Committee on Vaccine Safety (GACVS) concluded that the evidence did not support an increased risk of mortality after DTP immunization (WHO, 2004).

However, the onus of proof is surely the reverse of this—we need clear evidence that a vaccine is safe when it is given routinely to all infants in high-mortality areas. In addition, the Committee based its conclusion on observational studies, all of which had one or more serious methodological problems (Shann, 2010; Aaby et al., 2007; Fine et al., 2007; Jensen et al., 2007; Farrington et al., 2009). First, any observational study (with non random allocation of vaccines) may induce a spurious association between vaccination and survival (Farrington et al., 2009). Second, vaccination was often withheld in sick children, which causes selection bias in favor of DTP (Aaby et al., 2007). Third, many of the studies classified dead children as unvaccinated if there was no evidence they had been immunized; as some of these children will have been vaccinated, this causes survival bias in favor of DTP (Shann et al., 2010; Aaby et al., 2007; Fine

et al., 2007; Jensen et al., 2007; Farrington et al., 2009). Fourth, most of the studies did not test the effect of the most recent vaccine received by each child over time: the first dose of DTP has different effects when given before, with, or after BCG (Aaby et al., 2011; Aaby et al., 2007); the last dose of DTP has different effects given before, with, or after measles vaccine (Aaby et al., 2007; Aaby et al., 2003); and the effects differ by sex (Shann et al., 2010). Fifth, many children were given BCG at the same time as DTP, rather than at birth (6 weeks before DTP) as specified in the EPI schedule (Aaby et al., 2007). In 2008, GACVS finally endorsed the view that evidence for the safety of DTP is ‘‘unlikely to be obtained from observational studies’’ (WHO, 2008). Given the very large number of lives at stake, it is disappointing that it took the Committee so long to decide that observational studies are unlikely to provide adequate evidence that it is safe to give DTP to infants who have been vaccinated with BCG at birth, and even more disappointing that international agencies have not funded randomized trials to test the effect of DTP on all-cause mortality in children in high-mortality areas (Shann et al., 2010; Aaby et al., 2007). We could obtain this information while still immunizing against diphtheria, tetanus, and pertussis if we randomized children to receive the primary series of DTP at different ages, or to receive a booster dose of DTP at different ages (Shann et al., 2010; WHO, 2010).

The current EPI schedule is BCG-polio at birth; DTP-polio at 6, 10, and 14 weeks; and measles vaccine at 9 months–but tuberculosis, polio, diphtheria, tetanus, pertussis, and measles are not the main causes of death in children, even in unimmunized communities (Preston, 1976). The main reason that the EPI program has been beneficial may not be because it protects against these infections, but because the nonspecific effects of BCG and measles vaccines reduce the very large number of deaths from pneumonia, sepsis, and diarrhea. It is exciting that we may be

able to save several million more lives each year just by making better use of the current EPI vaccines in an improved schedule we urgently need randomized trials of the effects of the EPI vaccines on total mortality to help us design the optimal schedule (Shann et al., 2010; Aaby et al., 2007).

2.2 LOGISTIC REGRESSION

Logistic regression was used to predict the occurrence of intense/super-intense geomagnetic storms (Srivastava, 2005). In predicting the occurrence of intense/super-intense, a binary dependent variable, indicating the occurrence of intense/super-intense geomagnetic storms, was regressed against a series of independent model variables that define a number of solar and interplanetary properties of geo-effective CMEs. The model parameters (regression coefficients) were estimated from a training data set which was extracted from a dataset of 64 geo-effective CMEs observed during 1996–2002. The trained model was validated by predicting the occurrence of geomagnetic storms from a validation dataset, also extracted from the same data set of 64 geoeffective CMEs, recorded during 1996–2002, but not used for training the model. The model predicted 78% of the geomagnetic storms from the validation data set. In addition, the model predicted 85% of the geomagnetic storms from the training data set. These results indicated that logistic regression models can be effectively used for predicting the occurrence of intense geomagnetic storms from a set of solar and interplanetary factors (Srivastava, 2005).

Furthermore, logistic regression was used to predict diabetic retinopathy among diabetic patient (Senthilvel et al., 2011). In their study, a retrospective hospital based study was carried out in Aravind Eye Hospital, Thavalakuppam Puducherry(UT) during January-June 2011. One hundred diabetic patients were included by simple random sampling method into two groups: patients

with diabetic retinopathy and patients without diabetic retinopathy. They used the binary logistic regression for the prediction of diabetic retinopathy in a person. They considered a p-value of <0.05 as statistically significant. The results from their study revealed that the probability or chance for the individual to develop diabetic retinopathy was 0.98 (Senthilvel et al., 2011).

Also, it was used to determine health related factors that affect neonatal, post neonatal, infant and child mortality in Bangladesh (Chowdhury et al., 2009). For this, the data was collected using multistage sampling technique and direct method of mortality estimation, contingency analysis and logistic regression procedure has been applied. The results showed Multivariate analysis results designate immunization, types of delivery, medical check-up duration of pregnancy and health check-up for child have crucial influence on mortality of post-neonatal period but in infant and child period, immunization practices and treatment place of women have significant effects on mortality(Chowdhury et al., 2009).

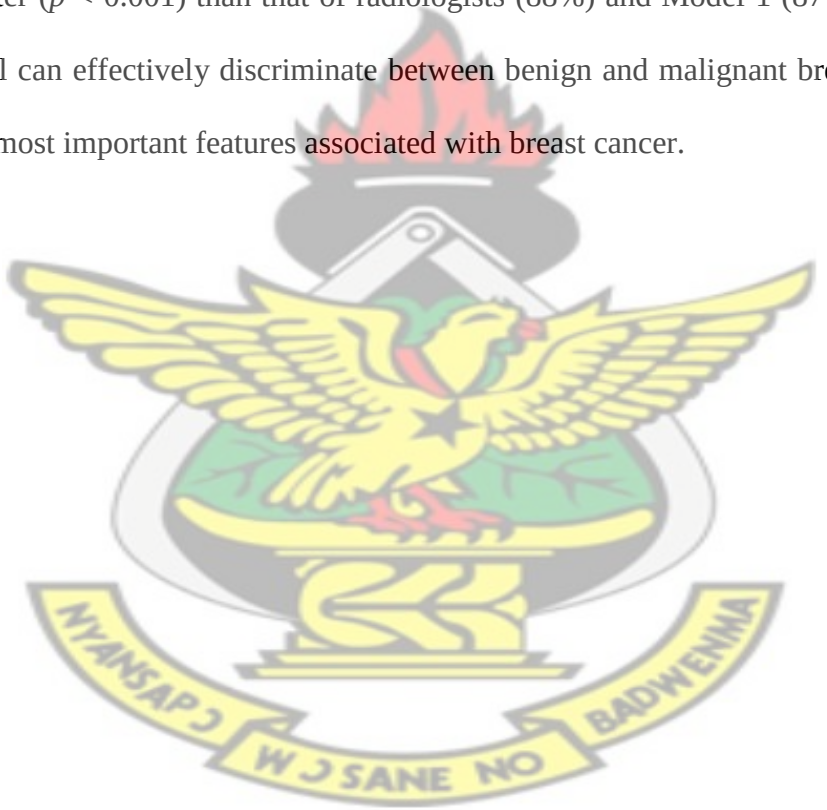
Moreover, Donalisio et al., 2006 used logistic regression to identify factors related to vaccination against influenza in the elderly population. A household survey was carried out using a systematic random sample (N=365) of the urban population older than 60 years from the city of Botucatu, Southeastern Brazil. A logistic regression model using vaccination in 2002 as the dependent variable was used. The following covariates were tested: sex, age, socioeconomic variables (per capita income, number of persons per dormitory, schooling, marital status, occupation, time living in the city), history of morbidity and hospital admission, smoking, respiratory symptoms in last 15 days, and community activities (voluntary work, neighborhood and church activities). Variables associated with vaccination in the final model were age (OR=1.09 per year; 95% CI: 1.06-1.13); arterial hypertension (OR=1.92; 95% CI: 1.18-3.13);

and participation in community activities (OR=1.63; 95% CI: 1.01-2.65). With the exception of hypertension, vaccination among subjects with chronic diseases did not reach adequate levels, as expected for this high-risk group. Participation in social and community activities was associated with vaccination status (Donalisio et al., 2006)

Goldhaber-Fiebert et al., 2010 used country-level, longitudinal panel data, from 44 countries over the period 1960–2005, they analyzed the relationship between measles containing vaccines (MCV) coverage and measles mortality with logistic regressions for no measles deaths in a country-year. Covariates included birth rate, death rates from other causes, percent living in urban areas, population density, per-capita GDP, use of the two-dose MCV, year, and mortality coding system. The likelihood of no measles deaths increased nonlinearly with higher MCV coverage (ORs: 13.8 [1.6–122.7] for 80–89% to 40.7 [3.2–517.6] for $95%), compared to pre-vaccination risk levels. Measles death rates declined nonlinearly with higher MCV coverage, with benefits accruing more slowly above 90% coverage (Goldhaber-Fiebert et al., 2010).

Chhatwal et al., 2009 used logistic regression to create a breast cancer risk estimation model based on the descriptors of the National Mammography Database that can aid in decision making for the early detection of breast cancer. They created two logistic regression models based on the mammography features and demographic data for 62,219 consecutive mammography records from 48,744 studies in 18,270 patients reported using the Breast Imaging Reporting and Data System (BI-RADS) lexicon and the National Mammography Database format between April 5, 1999 and February 9, 2004. State cancer registry outcomes were matched with data served as the reference standard. The probability of cancer was the outcome in both models. Model 2 was built

using all variables in Model 1 plus radiologists' BI-RADS assessment categories. They used 10-fold cross-validation to train and test the model and to calculate the area under the receiver operating characteristic curves (Az) to measure the performance. Both models were compared with the radiologists' BI-RADS assessments. Radiologists achieved an Az value of 0.939 ± 0.011. The Az was 0.927 ± 0.015 for Model 1 and 0.963 ± 0.009 for Model 2. At 90% specificity, the sensitivity of Model 2 (90%) was significantly better ($p < 0.001$) than that of radiologists (82%) and Model 1 (83%). At 85% sensitivity, the specificity of Model 2 (96%) was significantly better ($p < 0.001$) than that of radiologists (88%) and Model 1 (87%). The logistic regression model can effectively discriminate between benign and malignant breast disease and can identify the most important features associated with breast cancer.



CHAPTER THREE

3.0 METHODOLOGY

The longitudinal study that collects and update vaccination and death registration in the Dangme West District were analysed using bivariate and multivariate binary logistic regressions. Chi square and Fisher's exact test were used to test the association and the significance level that were considered is $\alpha=0.05$. The methodology chapter presents the study area, the study methods and design, the data storage and analyses, introduction to logistic regression, measures and ethical consideration.

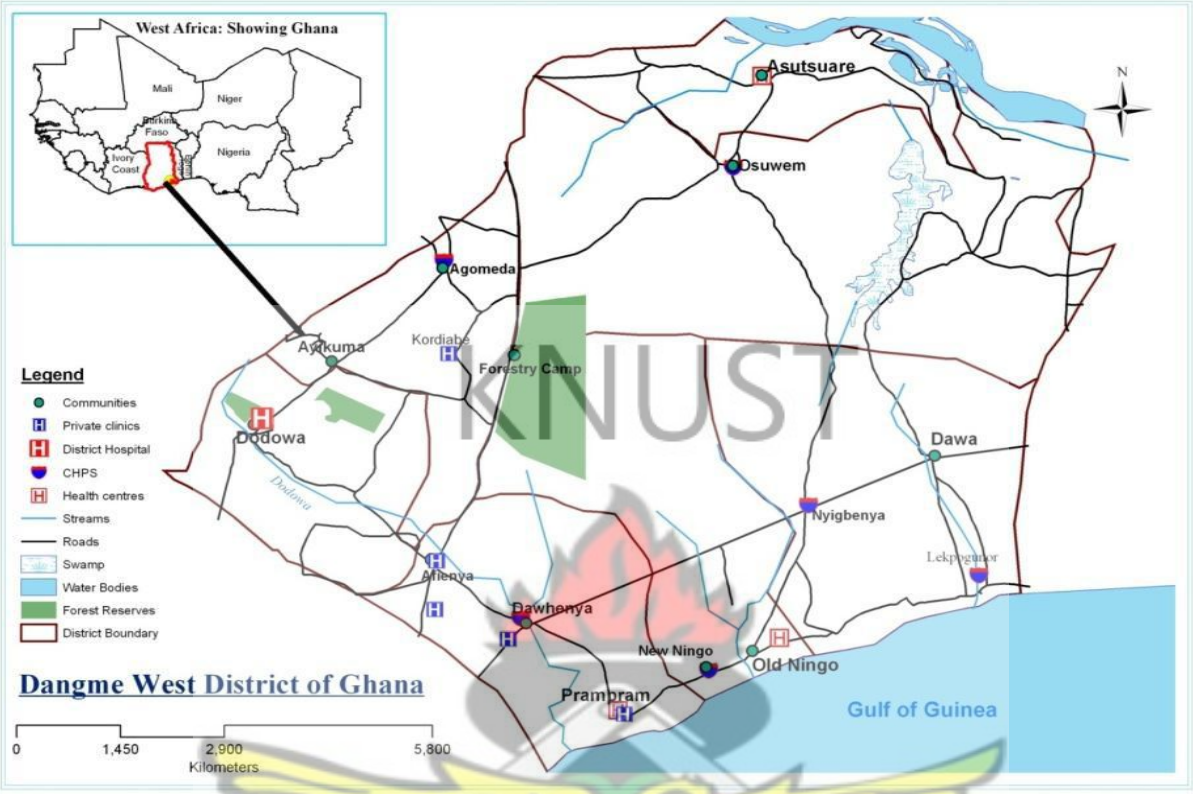
3.1 STUDY AREA

The Dangme West district is located in the Greater Accra Region of Ghana. The district covers a land surface area of about 1529 square kilometers and the vegetation is mainly coastal savannah. The district is divided into seven administrative area councils– Asutsuare, Ayikuma, Dodowa, Dawa, Ningo, Osuwem and Prampram. However, for the purposes of health delivery, there are four sub-districts Dodowa, Osudoku, Prampram and Ningo. Poverty is widespread in the district.

There is a 50-bed district hospital, four health centres and 10 CHPS compounds and about 150 outreach in the public sector. In addition there are a mission hospital and a quasi-Government hospital and 5 private facilities comprising 3 clinics and 2 maternity homes. All these facilities collaborate with, and submit annual reports to the District Health Management Team. The district hospital is the main referral facility. However, some referrals are also made to facilities outside the district such as Tema General Hospital and Ridge Hospital. Laboratory facilities are available at the district hospital, one health centre (Osudoku) and one private clinic. There are 3 pharmacy shops and 55 licensed chemical shops.

The Dodowa Health Research Centre (DHRC) maintains a Health and Demographic Surveillance System, a longitudinal population registration system that serves the district. Vital demographic events such as births, deaths, pregnancies and migration are updated bi-annually. Vaccination and socio-demographic characteristics are collected annually. Verbal autopsies are conducted to elucidate the circumstances surrounding and possible causes of all recorded deaths. In order to enhance spatial analysis of the data being collected, Geographic Information System (GIS) has been incorporated into the HDSS activities. Routine HDSS data collection is performed by field workers who receive regular training for a period of 2 to 3 weeks between data collection rounds. The district has a population of 108,371 in 2010 under surveillance who live in 22,910 households in 380 scattered communities. 54% of the population has had some level of education. As at the end of the year 2009, 50% of the households had registered with the District Health Insurance Scheme. About 60% of the households own mobile phones. Farming and fishing are the main occupations for the residents living within the district.

Figure 3.1: A map showing Dangme West District of Ghana



Source: DHRC

3.2 STUDY SAMPLE AND DESIGN

The study was carried out as part of a longitudinal data collection in DHDSS. All children who were born between 2005 and 2009 were enrolled in the survey and update their vaccination data at the beginning of every round. These children were observed till 31st of December 2010 where their status (alive or dead) was recorded. For the purpose of this study, we used data from children born between 2005 and 2009 who were successfully follow-up and were expected to have received all the WHO-recommended vaccinations. The vaccination details were collected during the first registration of all 2 years and below. Full vaccination was defined as receiving all the basic childhood vaccinations. All vaccination data were obtained from vaccination cards which were sighted during the household visit.

3.3 DATA STORAGE AND ANALYSIS

The survey questionnaires were entered in HRS2. STATA 11 Software was used to analyse data. Descriptive statistics, bivariate and multivariate logistics were used to compare and identify the risk factors associated with incomplete/partial vaccination/immunisation.

3.4.0 INTRODUCTION TO LOGISTIC REGRESSION

Logistic regression methods have become an integral component of any data analysis concerned with describing the relationship between a response/outcome variable and one or more explanatory/independent variables. It is often the case that the outcome variable is discrete, taking on two or more possible values. Over the decade the logistic regression model has become, in many fields, the standard method of analysis in this situation. It is a mathematical modeling procedure used in the analysis of epidemiologic data. The logistic model is mostly used because the logistic function, on which the model is based, provides:

(a) Estimates that must lie in the range between zero and one

(b) An appealing S-shaped description of the combined effect of several risk factors on the risk for a disease.

The goal of logistic regression is to find the best fitting and most parsimonious, yet biologically reasonable model to describe the relationship between an outcome (dependent or response) variable and a set of independent (predictor or explanatory) variables. These independent variables are often called covariates.

What distinguish a logistic regression model from the linear model is that the outcome variable in logistic regression is binary or dichotomous whiles linear regression outcome variable is continuous. Also, the difference between logistic and linear regression model is reflected both in the choice of a parametric model and in the assumptions.

Many distribution functions have been proposed for use in the analysis of a dichotomous outcome variable (Cox et al., 1989). Firstly, from a mathematical point of view, it is an extremely flexible and easily used function, and secondly, it lends itself to a clinically meaningful interpretation.

The quantity $\pi(x) = E(Y|x)$ represents the conditional mean of $Y\ given\ x$ when the logistic distribution is used. The specific form of the logistic regression model is

$$\pi(x) = \frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}$$

A transformation of $\pi(x)$ that is central to our study of the logistic regression is the logit transformation. This transformation is defined, in terms of $\pi(x)$, as:

$$g(x) = \ln\left\{\frac{\pi(x)}{[1-\pi(x)]}\right\}$$

$$= \ln\left\{\frac{\frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}}{\left[1-\frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}\right]}\right\}$$

$$= \ln\left\{\frac{\frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}}{\left[\frac{1+e^{\beta_0+\beta_1 x}-e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}\right]}\right\}$$

$$= \ln\left\{\frac{\frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}}{\left[\frac{1+\cancel{e^{\beta_0+\beta_1 x}}-\cancel{e^{\beta_0+\beta_1 x}}}{1+e^{\beta_0+\beta_1 x}}\right]}\right\}$$

$$= \ln\left\{\frac{\frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}}{\left[\frac{1}{1+e^{\beta_0+\beta_1 x}}\right]}\right\}$$

$$= ln\left\{\frac{e^{\beta_0+\beta_1 x}}{\cancel{1+e^{\beta_0+\beta_1 x}}} \times \frac{\cancel{1+e^{\beta_0+\beta_1 x}}}{1}\right\}$$

$$= ln\left\{\frac{e^{\beta_0+\beta_1 x}}{1}\right\}$$

$$= \beta_0 + \beta_1 x$$

The importance of this transformation is that $g(x)$ has many of the desirable properties of a linear regression model. The logit, $g(x)$, is linear in its parameters, may be continuous, and may range from $-\infty\ to\ +\infty$, depending on the range of x. The second importance difference between the linear and logistic regression models concerns the conditional distribution of the outcome variable.

In the linear regression model we assume that an observation of the outcome variable may be expressed as $y = E(Y|x) + \varepsilon$. The quantity ε, is called the error and expresses an observation's deviation from the conditional mean. The assumption is that ε follows a normal distribution with mean zero and some variable that is constant across levels of the independent variable. It follows

that the conditional distribution of the outcome variable given x will be normal with mean $E(Y|x)$, and a variance that is constant.

In logistic regression model, the outcome variable is expressed as $y = \pi(x) + \varepsilon$. Here the outcome quantity ε may assume one of two possible values. If $y = 1$ then $\varepsilon = 1 - \pi(x)$ with probability $\pi(x)$, and if $y = 0$ then $\varepsilon = -\pi(x)$ with probability $1 - \pi(x)$. Thus, ε has a distribution with mean zero and variance equal to $\pi(x)[1 - \pi(x)]$. That is, the conditional distribution of the outcome variable follows a binomial distribution with probability given by the conditional mean, $\pi(x)$

In regression analysis when the outcome variable is dichotomous, the conditional mean of the regression equation must be formulated to be bounded between zero(0) and one(1). The binomial, not the normal, distribution describes the distribution of the errors and will be the statistically distribution upon which the analysis is based. The principles that guide an analysis using linear regression will also guide in logistic regression.

3.4.1 FITTING THE LOGISTIC REGRESSION MODEL

Suppose we have a sample of n independent observations of the pair$(x_i, y_i), i = 1,2, \dots, n$, where y_i denotes the value of a dichotomous outcome variable and x_i is the value of the independent variable for the i^{th} subject. Furthermore, assume the outcome variable has been coded as 0 or 1, representing the absence or the presence of the characteristics, respectively. To fit the logistic regression model to a set of data requires that we estimate the values of β_0 and β_1, then unknown parameters.

In logistic regression model, the maximum likelihood estimators are used to determine the parameters that are chosen to be those values that maximize this function. If Y is coded as 0 or 1 then the expression for $\pi(x)$ provides (for an arbitrary value of $\beta = (\beta_0, \beta_1)$, the vector of parameters) the conditional probability that Y is equal to 1 given x. This will be denoted as $P(Y = 1|x)$. It follows that the quantity $1 - \pi(x)$ gives the conditional probability that Y is equal to 0 given x, $P(Y = 0|x)$. Thus, for those pairs(x_i, y_i), where $y_i = 1$, the contribution to the likelihood function is $\pi(x_i)$, and for those pairs where $y_i = 0$, the contribution to the likelihood function is $1 - \pi(x_i)$, where the quantity $\pi(x_i)$ denotes the value of $\pi(x)$ computed at x_i. A convenient way to express the contribution to the likelihood function for the pair (x_i, y_i) is through the expression

$$\pi(x_i)^{y_i}[1 - \pi(x_i)]^{1-y_i}$$

Since the observations are assumed to be independent, the likelihood function is obtained as the product of the terms given in expression above as follows:

$$l(\beta) = \prod_{i=1}^{n} \pi(x_i)^{y_i} [1 - \pi(x_i)]^{1-y_i}$$

The principle of maximum likelihood states that we use as our estimate of β the value which maximizes the expression $l(\beta)$. However, it is easier mathematically to work with the log of equation $l(\beta)$. This expression, the log likelihood, is defined as

$$L(\beta) = \ln[l(\beta)] = \sum_{i=1}^{n}\{y_i \ln[\pi(x_i)] + (1 - y_i)\ln[1 - \pi(x_i)]\}.$$

To find the value of β that maximizes $L(\beta)$ we differentiate $L(\beta)$ with respect to β_0 and β_1 and set the resulting expressions equal to zero.

These equations, known as the likelihood equations, are:

$$\sum_{i=1}^{n}[y_i - \pi(x_i)] = 0$$

and

$$\sum_{i=1}^{n} x_i[y_i - \pi(x_i)] = 0$$

The above equations are shown using an iterative weighted least squares procedure (McCullagh et al., 1989).

The value of β given by the solution is called the maximum likelihood estimate and will be denoted as $\hat{\beta}$. In general, the use of the symbol "^" denotes the maximum likelihood estimates of the respective quantity. $\hat{\pi}(x_i)$ is the maximum likelihood estimates of $\pi(x_i)$. This quantity provides an estimate of the conditional probability that Y is equal to 1, given that c is equal to x_i. As such, it represents the fitted or predicted value for the logistic regression model. An interesting consequence of the equation

$$\sum_{i=1}^{n}[y_i - \pi(x_i)] = 0$$

is that

$$\sum_{i=1}^{n} y_i = \sum_{i=1}^{n} \hat{\pi}(x_i)$$

That is, sum of the observed values of y is equal to the sum of the predicted (expected) values.

3.4.2 TESTING FOR THE SIGNIFICANCE OF THE COEFFICIENTS

In logistic regression, comparison of observed to predicted values is based on the log likelihood function. A saturated model is a model that contains as many parameters as there are data points. The comparison of observed to predicted values using the likelihood function is based on the following expression:

$$D = -2\ln\left[\frac{(likelihood\ of\ the\ fitted\ model)}{(likelihood\ of\ the\ saturated\ model)}\right]$$

The quantity inside the large brackets in the expression above is called the likelihood ratio. Using minus twice its log is necessary to obtain a quantity whose distribution is known and can therefore be used for hypothesis testing purposes. Such test is called the likelihood ratio test and this is stated as

$$D = -2\sum_{i=1}^{n}\left[y_i \ln\left(\frac{\hat{\pi}(x_i)}{y_i}\right) + (1-y_i)\ln\left(\frac{1-\hat{\pi}(x_i)}{1-y_i}\right)\right]$$

The statistic, D, in the equation above is called the deviance (McCullagh et al., 1989), and plays a central role in some approaches to assessing goodness-of-fit. The deviance shown above is

identically equal to the residual sum of squares in linear regression in the context of testing for the significance of the fitted model.

When assessing the significance of an independent variable we compare the value of D with or without the independent variable in the equation. The change in D due the inclusion of the independent variable in the model is obtained as:

$$G = D(model\ without\ the\ variable) - D(model\ with\ the\ variable).$$

This statistics plays the same role in logistic regression as the numerator of the partial F test does in linear regression. Because the likelihood of the saturated model is common to both values of D being differenced to compute G, it can be expressed as

$$G = -2\ln\left[\frac{(likelihood\ without\ the\ variable)}{(likelihood\ with\ the\ variable)}\right]$$

For the specific case of a single independent variable, it is easy to show that when the variable is not in the model , the maximum likelihood estimate of

$$\beta_0 = ln\left(\frac{n_1}{n_0}\right) \quad where\ n_1 = \sum y_i \quad and\ n_0 = \sum(1 - y_i)$$

And the predicted value is constant, $\frac{n_1}{n}$. In this case, the value of G is:

$$G = -2ln\left[\frac{\left(\frac{n_1}{n}\right)^{n_1}\left(\frac{n_0}{n}\right)^{n_0}}{\prod_{i=1}^{n}\hat{\pi}_i^{y_i}(1-\hat{\pi}_i)^{1-y_i}}\right]$$

Or

$$G = 2\left\{\sum_{i=1}^{n}[y_i \ln(\hat{\pi}_i) + (1-y_i)\ln(1-\hat{\pi}_i)] - [n_1 \ln(n_1) + n_0 \ln(n_0) - nln(n)]\right\}$$

Under the hypothesis that β_1 is equal to zero, the statistic G follows a chi-square distribution with 1 degree of freedom. Additional mathematical assumptions are also needed; however, for the above case they are rather nonrestrictive and involve having a sufficient large sample size, n.

3.4.3 THE WALD TEST

The Wald test is obtained by comparing the maximum likelihood estimate of the slope parameter, $\hat{\beta}_1$, to an estimate of its standard error. The resulting ratio, under the hypothesis that $\beta_1 = 0$, will follow a standard normal distribution. The Walt test is stated mathematically as

$$W = \frac{\hat{\beta}_1}{\widehat{SE}(\hat{\beta}_1)}$$

Hauck et al., 1977 examined the performance of the Wald test and found that it behaved in an aberrant manner, often failing to reject the null hypothesis when the coefficient was significant. They recommend that the likelihood ratio test be used.

Jennings, 1986 has also looked at the adequacy of inferences in logistic regression based on Wald statistics. His conclusions are similar to those of Hauck et al., 1977. Both the likelihood ratio test, G, and the Wald test, W, require the computation of the maximum likelihood estimate for β_1

3.4.4 THE SCORE TEST

The Score test is based on the distribution theory of the derivatives of the log likelihood. It is a multivariate test requiring matrix calculations. In a univariate case, this test is based on the conditional distribution of the derivative in

$$\sum_{i=1}^{n} x_i[y_i - \pi(x_i)] = 0,$$

given the derivative in

$$\sum_{i=1}^{n} [y_i - \pi(x_i)] = 0$$

.

Assume that $\beta_0 = ln\left(\frac{n_1}{n_0}\right)$, $\beta_1 = 0$ and $\hat{\pi} = \frac{n_1}{n} = \bar{y}$, the test statistics for the Score test (ST) is stated mathematically as

$$ST = \frac{\sum_{i=1}^{n} x_i(y_i - \bar{y})}{\sqrt{\bar{y}(1-\bar{y})\sum_{i=1}^{n}(x_i - \bar{x})^2}}$$

3.4.5 THE CONFIDENCE INTERVAL ESTIMATION

The basis of construction of the interval estimators is the same statistically theory we used to formulate the tests for significance of the model. The confidence interval estimators for the slope and intercept are based on their respective Wald tests. The endpoints of a $100(1-\alpha)\%$ confidence interval for the slope coefficient are

$$\hat{\beta}_1 \pm Z_{1-\frac{\alpha}{2}}\widehat{SE}(\hat{\beta}_1)$$

And for the intercept they are

$$\hat{\beta}_0 \pm Z_{1-\frac{\alpha}{2}}\widehat{SE}(\hat{\beta}_0)$$

Where $Z_{1-\frac{\alpha}{2}}$ is the upper $100\left(1-\frac{\alpha}{2}\right)\%$ point from the standard normal distribution and $\widehat{SE}(.)$ denotes a model-based estimator of the standard error of the respective estimator.

3.4.6 INTERPRETATION OF THE FITTED LOGISTIC REGRESSION MODEL

The first step is to determine what function of the dependent variable yields a linear function of the independent variables. This is known as the link function (McCullagh et al., 1989; Dobson, 1990). In the case of a linear regression model, it is the identity function since the dependent variable, by definition, is linear in the parameters. In the logistic regression model the link function is the logit transformation

$$g(x) = \ln\left\{\frac{\pi(x)}{[1-\pi(x)]}\right\} = \beta_0 + \beta_1 x$$

In the logistic regression model, the slope coefficient represents the change in the logit corresponding to a change of one unit in the independent variable.

3.4.7 THE DICHOTOMOUS INDEPENDENT VARIABLE

Here we assume that the independent variable, x, is coded as either zero or one. The difference in the logit for a subject with x=1 and x=0 is

$$g(1) - g(0) = (\beta_0 + \beta_1) - \beta_0 = \beta_1$$

The logit difference is equal to β_1.

The odds of the outcome being present among individuals with x=1 is defined as

$$\frac{\pi(1)}{[1-\pi(1)]}$$

Similarly, the odds of the outcome being present among individuals with x=0 is defined as

$$\frac{\pi(0)}{[1-\pi(0)]}$$

The odds ratio, denoted OR, is defined as the ratio of the odds for x=1 to the odds for x=0 and is given by the equation

$$OR = \frac{\frac{\pi(1)}{[1-\pi(1)]}}{\frac{\pi(0)}{[1-\pi(0)]}}$$

Substituting the expressions for the logistic regression model is shown in Table 3.1 into OR we obtain

Table 3.1 Values of the logistic Regression Model When the Independent Is Dichotomous

Outcome Variable(Y)	Independent variable(X)	
	$x = 1$	$x = 0$
$y = 1$	$\pi(1) = \frac{e^{\beta_0+\beta_1}}{1+e^{\beta_0+\beta_1}}$	$\pi(0) = \frac{e^{\beta_0}}{1+e^{\beta_0}}$
$y = 0$	$1-\pi(1) = \frac{1}{1+e^{\beta_0+\beta_1}}$	$1-\pi(0) = \frac{1}{1+e^{\beta_0}}$
Total	**1.0**	**1.0**

$$OR = \frac{\left(\frac{e^{\beta_0+\beta_1}}{1+e^{\beta_0+\beta_1}}\right) \Big/ \left(\frac{1}{1+e^{\beta_0+\beta_1}}\right)}{\left(\frac{e^{\beta_0}}{1+e^{\beta_0}}\right) \Big/ \left(\frac{1}{1+e^{\beta_0}}\right)}$$

$$OR = \frac{e^{\beta_0+\beta_1}}{e^{\beta_0}}$$

$$OR = e^{(\beta_0+\beta_1)-\beta_0}$$

$$OR = e^{\beta_1}$$

Hence, for logistic regression with a dichotomous independent variable coded 1 and 0, the relationship between the odds ratio and the regression coefficient is

$$\boldsymbol{OR} = \boldsymbol{e^{\beta_1}}$$

This simple relationship between the coefficient and the odds ratio is the fundamental reason why logistic regression has proven to be such a powerful analytic research tool.

The interpretation given for the odds ratio is based on the fact in many instances it approximates a quantity called the relative risk. The odds ratio approximates the relative risk if

$$[1-\pi(0)] / [1-\pi(1)] \approx 1$$

This holds when $\pi(x)$ is small for both x=1 and 0 (Breslow et al., 1980; Kelsey et al., 1986, Rothman et al., 1998; Schlesselman, 1982).

A $100 \times (1-\propto)\%$ confidence interval (CI) estimate for the odds ratio is obtained by first calculating the endpoints of the confidence interval for the coefficient, β_1 and then exponentiation these values. In general, the endpoints are given by the expression

$$\exp\left[\hat{\beta}_1 \pm z_{1-\frac{\alpha}{2}} \times \widehat{SE}(\hat{\beta}_1)\right]$$

3.4.8 TYPE OF DICHOTOMOUS INDEPENDENT VARIABLE CODING

There are two types of dichotomous independent variable coding. They are: reference coding and deviation from the mean coding.

3.4.8.1 REFERENCE CELL CODING

The reference cell coding assigns the value of zero to the lower code and 1 to the higher code.

Table 3.2: Illustration of the coding of the design variable using reference cell coding

Vaccination (code)	Design Variable
Fully vaccinated/immunised(1)	0
Partially vaccinated/immunised(2)	1

3.4.8.2 DEVIATION FROM THE MEAN CODING

This method assigns the value of -1 to the lower code and a value of 1 to the higher code.

Table 3.3: Illustration of the coding of the design variable using deviation from the mean coding

Vaccination (code)	Design Variable
Fully vaccinated/immunised(1)	-1
Partially vaccinated/immunised(2)	1

Suppose we wish to estimate odds ratio of fully immunised versus partially immunised when deviation from the means coding is used. This is shown mathematically as

$$\ln\left[\widehat{OR}\ (\text{Partially immunised, Fully immunised})\right]$$

$$= \hat{g}(\text{Partially immunised}) - \hat{g}(\text{Fully immunised})$$

$$= g(D = 1) - g(D = -1)$$

$$= [\hat{\beta}_0 + \hat{\beta}_1 \times (D = 1)] - [\hat{\beta}_0 + \hat{\beta}_1 \times (D = -1)]$$

$$= 2\hat{\beta}_1$$

Therefore,

The estimated odds ratio is $\widehat{OR}\ (\text{Partially immunised, Fully immunised}) = \exp\ (2\hat{\beta}_1)$.

Thus the end points of the confidence interval are

$$\exp\ [2\hat{\beta}_1 \pm z_{1-\frac{\alpha}{2}} \times 2\widehat{SE}(\hat{\beta}_1)]$$

In general, the endpoints of the confidence interval for the odds ratio is

$$\exp\ [\hat{\beta}_1(a-b) \pm z_{1-\frac{\alpha}{2}} \times |a-b| \times \widehat{SE}(\hat{\beta}_1)]$$

3.5 MEASURES

There are two types of measures. These are outcome and exposures measures.

3.5.1 OUTCOME MEASURES

The outcome or dependent variable is the status of a child as at 2010 [child died=1 and child alive=0]

3.5.2 EXPOSURE MEASURES

The following covariates variables of interest were examined:

(i) immunization status of child categorised as fully immunised/vaccinated, Partially immunised/vaccinated

(ii) sex of the child assessed as male and female

(iii) age of child regrouped as 12-23 months, 24-35 months, 36-47 months3, 48-59 months, 60-71 months

(iv) Place of birth group as Health facility, Traditional Birth Attendant (TBA) and Home.

(v) birth order assessed as first birth and non-first birth

(vi) mothers' age, grouped as less than 18 years, 18-29 years, 30-39 years, 40-49 years, 50-59 years and 60+ years

(vii) mothers' marital status, grouped as single, currently married and formally married

(viii) mothers' education, categorised as No education, primary and secondary

(ix) mothers' occupation categorised as Not working, farmer, artisan, trader, civil servant, student and others

(x) mother's household wealth index, categorised into five quintiles

3.6 ETHITICAL CONSIDERATIONS

This study is based on analysis of secondary data with all participants' identifiers removed. The survey was approved by the Ghana Health Service Ethics Committee. Verbal informed consent was obtained from the participants prior to participation in the survey, and data collection was done confidentially. Permission to use the HDSS data in this study was obtained from DHRC.

CHAPTER FOUR

4.0 DATA COLLECTION AND ANALYSIS

The results chapter presents the study population, demographic background of the child, socio-demographic background of the mothers/caretakers and factors that affect immunization of child mortality.

4.1 STUDY POPULATION

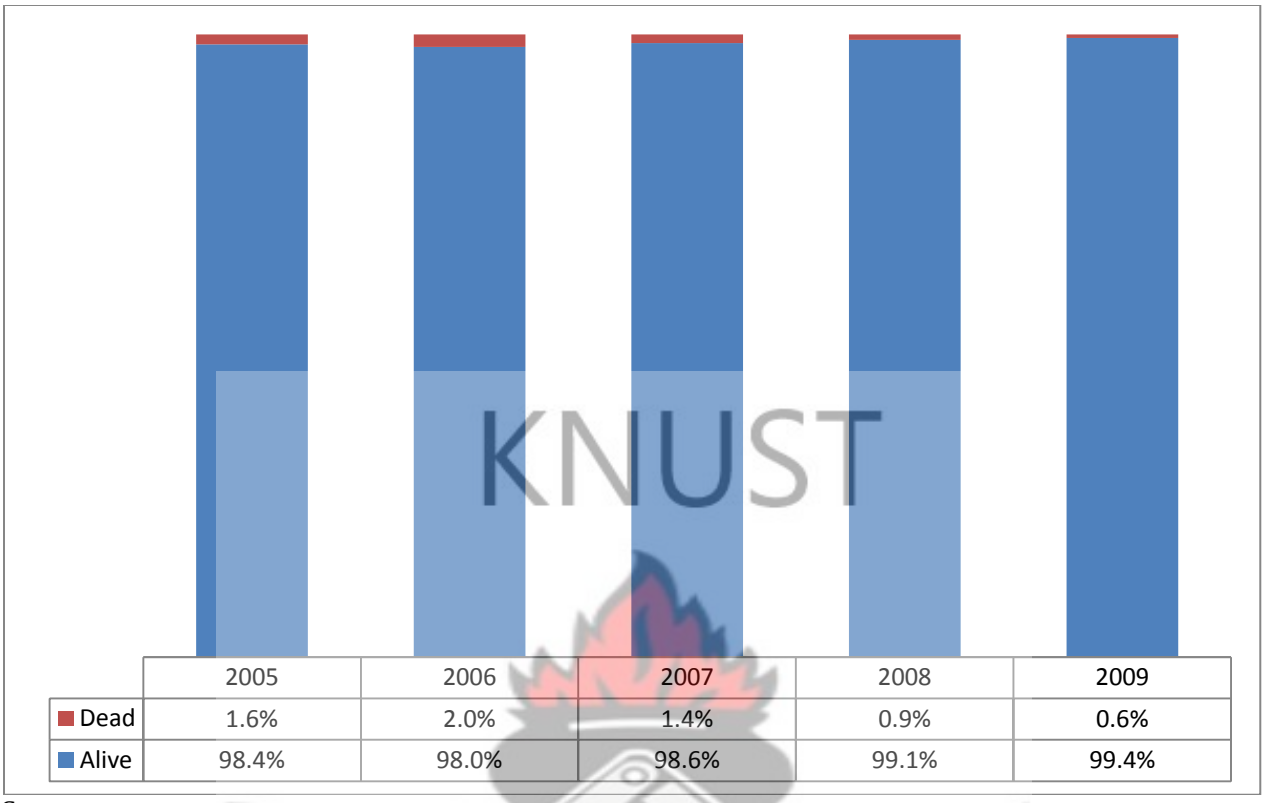
A total of 13 915 children were born from 2005 to 2009. All these children were follow-up till 31st of December 2010. A total of 3 463(24.9%) children migrated to another district (Out migration). The total number of children living within the district as at 31st of December 2010 is 10 452. Out of this number, 132(1.3%) of the children died before their first birthday, hence have been excluded from the analysis. Table 4.1 shows the year in which the children were born by the status of health card. From Table 4.1, about three-quarters of the children's health cards were seen by the data collectors. 21.8% of the health card was not seen by the data collectors at the time of the interview although the caretakers' or mothers' of the children indicated that their children have the health card. The remaining 279(2.7%) of the children do not have the health card.

Table 4.1: Year born by status of health card.

	Health Card Information			
Year	Have health card and seen by Data collectors	Have health card but not available[Health card not seen by Data collectors]	Do not have health card	Total
2005	1295 (67.5)	590 (30.8)	33 (1.7)	1918 (100.0)
2006	1510 (73.4)	499 (24.3)	48 (2.3)	2057 (100.0)
2007	1643 (78.9)	381 (18.3)	58 (2.8)	2082 (100.0)
2008	1831 (80.8)	357 (15.8)	77 (3.4)	2265 (100.0)
2009	1517 (75.9)	418 (20.9)	63 (3.2)	1998 (100.0)
Total	7796 (75.5)	2245 (21.8)	279 (2.7)	10320 (100.0)

Source: DHDSS & DHRC 2011

Figure 4.1 depicts the children year of birth and their status (alive or dead) at follow-up as at December 2010. From Figure 4.1 it is evident that when the child is followed up for a longer period the more deaths we are likely to record. This is statistically significant (p=0.001 and Pearson chi-square value (χ^2) = 18.6709)



	2005	2006	2007	2008	2009
Dead	1.6%	2.0%	1.4%	0.9%	0.6%
Alive	98.4%	98.0%	98.6%	99.1%	99.4%

Source: Source: DHDSS & DHRC 2011

Figure 4.1: Children year of birth by their status (alive or dead) as at 31st December 2010.

4.2 IMMUNIZATION/VACCINATION COVERAGE

The analysis is only limited to children whose health cards were seen by data collectors. Table 4.2 shows the immunization coverage by year of birth. Fully immunised children who were born 2005-2009 vary from 85.4% to 52.1%. The highest fully immunised coverage were children born in 2005 and the least were the children born in 2008. The overall fully immunised coverage for the children in the Dangme West District of Ghana is 67.6% as at December 2010 follow-up.

Table 4.2: Immunization coverage of children by their year of birth

	2005			2006			2007			2008			2009			Overall		
	Alive	Dead	Total	Alive	Dead	Total	Alive	Dead	Total	Alive	Dead	Total	Alive	Dead	Total	Alive	Dead	Total
N	**1274**	**21**	**1295**	**1485**	**25**	**1510**	**1620**	**23**	**1643**	**1815**	**16**	**1831**	**1509**	**8**	**1517**	**7703**	**93**	**7796**
BCG (0)	1255 (98.5)	21 (100.0)	1276 (98.5)	1474 (99.3)	24 (96.0)	1498 (99.2)	1620 (99.4)	23 (100.0)	1629 (99.2)	1792 (98.7)	15 (93.8)	1807 (98.7)	1495 (99.1)	8 (100.0)	1503 (99.1)	7622 (99.0)	91 (97.9)	7713 (98.9)
Polio (0)	742 (58.3)	8 (38.1)	750 (58.0)	872 (58.7)	15 (60.0)	887 (58.7)	981 (60.6)	15 (65.2)	996 (60.6)	1182 (65.1)	10 (62.5)	1192 (65.1)	1013 (67.1)	5 (62.5)	1517 (67.1)	4790 (62.2)	53 (57.0)	4843 (62.1)
Polio 1	1262 (99.1)	21 (100.0)	1283 (99.1)	1457 (98.1)	22 (88.0)	1479 (98.0)	1546 (95.4)	22 (95.7)	1568 (95.4)	1685 (92.8)	14 (87.5)	1699 (92.8)	1424 (94.4)	8 (100.0)	1432 (94.4)	7374 (95.7)	87 (93.6)	7461 (95.7)
Polio 2	1242 (97.5)	21 (100.0)	1263 (97.5)	1407 (94.8)	21 (84.0)	1428 (94.6)	1482 (91.5)	21 (91.3)	1503 (91.5)	1583 (87.2)	13 (81.3)	1596 (87.2)	1330 (88.2)	8 (100.0)	1338 (88.3)	7044 (91.5)	84 (90.3)	7128 (91.4)
Polio 3	1172 (92.0)	20 (95.2)	1192 (92.1)	1310 (88.2)	18 (72.0)	1328 (88.0)	1398 (86.3)	18 (78.3)	1416 (86.2)	1420 (78.2)	11 (68.8)	1431 (78.2)	1219 (80.8)	6 (75.0)	1225 (80.8)	6519 (84.6)	73 (78.5)	6592 (84.6)
DPT 1	1258 (98.7)	21 (100.0)	1279 (98.8)	1452 (97.8)	23 (92.0)	1475 (97.8)	1545 (95.4)	22 (95.7)	1567 (95.4)	1678 (92.5)	14 (87.5)	1692 (92.5)	1407 (93.2)	8 (100.0)	1415 (93.3)	7340 (95.3)	88 (94.6)	7428 (95.3)

BCG (0) means BCG at birth; Polio (0) means Polio at birth

Table 4.2: Immunization coverage of children by their year of birth (continued)

	2005			2006			2007			2008			2009			Overall		
	Alive	Dead	Total	Alive	Dead	Total	Alive	Dead	Total	Alive	Dead	Total	Alive	Dead	Total	Alive	Dead	Total
N	**1274**	**21**	**1295**	**1485**	**25**	**1510**	**1620**	**23**	**1643**	**1815**	**16**	**1831**	**1509**	**8**	**1517**	**7703**	**93**	**7796**
DPT 2	1241 (97.4)	21 (100.0)	1262 (97.5)	1410 (95.0)	21 (84.0)	1431 (94.8)	1490 (92.0)	20 (87.0)	1510 (91.9)	1581 (87.2)	13 (81.3)	1594 (87.1)	1334 (88.4)	8 (100.0)	1342 (88.5)	7056 (91.6)	83 (89.3)	7139 (91.6)
DPT 3	1209 (94.9)	20 (95.2)	1229 (94.9)	1354 (91.2)	20 (80.0)	1374 (91.0)	1436 (88.6)	20 (87.0)	1456 (88.6)	1434 (79.0)	11 (68.8)	1445 (78.9)	1242 (82.3)	6 (75.0)	1248 (82.3)	6675 (86.7)	77 (82.8)	6752 (86.6)
Measles	1171 (91.9)	18 (85.7)	1189 (91.8)	1238 (83.4)	14 (56.0)	1252 (82.9)	1249 (77.1)	15 (65.2)	1264 (76.9)	1000 (55.1)	4 (25.0)	1004 (54.8)	915 (60.6)	3 (37.5)	918 (60.5)	5573 (72.4)	54 (58.1)	5627 (72.2)
YF	1170 (91.8)	18 (85.7)	1188 (91.7)	1237 (83.3)	14 (56.0)	1251 (82.9)	1246 (76.9)	15 (65.2)	1261 (76.8)	998 (55.0)	4 (25.0)	1002 (54.7)	911 (60.4)	3 (37.5)	914 (60.3)	5562 (72.2)	54 (58.1)	5616 (72.2)
*All	1088 (85.4)	18 (85.7)	1106 (85.4)	1153 (77.6)	12 (48.0)	1165 (77.2)	1174 (72.5)	14 (60.9)	1188 (72.3)	950 (52.3)	4 (25.0)	954 (52.1)	857 (56.8)	3 (37.5)	860 (56.7)	5222 (67.8)	51 (54.8)	5273 (67.6)
**All	1083 (85.0)	18 (85.7)	1101 (85.0)	1150 (77.4)	12 (48.0)	1162 (77.0)	1169 (72.2)	14 (60.9)	1183 (72.0)	947 (52.2)	4 (25.0)	951 (51.9)	851 (56.4)	3 (37.5)	854 (56.3)	5200 (67.5)	51 (54.8)	5251 (67.4)

*Excludes Polio at birth and YF; ** Excludes Polio at birth only

Source: Source: DHDSS & DHRC 2011

4.3 BACKGROUND CHARATERISTICS OF CHILDREN AND THEIR CARETAKERS / MOTHERS

In Table 4.3a or 4.3b, the female children (68%) are more likely to fully immunised compared to the male children (67%). However, this is not statistically significant. For the deceased children, it was 52% for the females and 57% of the males that were fully immunised. There is no statistical difference between child's place of birth and their immunization status. First time mothers have a lower percentage of fully immunizing their children as compared to non-first time mothers. Fifty nine percent (59%) of First time mothers' children have been fully immunised and 66% of the fully immunised children were non-first time mothers. Thirty three percent (33%) and 50% of the deceased children who were fully immunised were respectively the first time mothers and non-first time mothers. Mothers who are currently married or had ever married are also more likely to fully immunised their child as compared to the single mother's.

Table 4.3a: Background characteristics of children

Variables	Alive Fully Immunised			Dead Fully Immunised			Total Fully Immunised		
	Yes n(%)	**No n(%)**	**Total N(%)**	**Yes n(%)**	**No n(%)**	**Total N(%)**	**Yes n(%)**	**No n(%)**	**Total N(%)**
Sex									
Female	2567 (68.3)	1191 (31.7)	3758 (100)	17 (51.5)	16 (48.5)	33 (100)	2584 (68.2)	1207 (31.8)	3791 (100)
Male	2654 (67.3)	1289 (32.7)	3943 (100)	34 (56.7)	26 (43.3)	60 (100)	2688 (67.2)	1315 (32.8)	4003 (100)
Place of birth									
Health facility	2351 (64.9)	1272 (35.1)	3623 (100)	13 (37.1)	22 (62.9)	35 (100)	2364 (64.6)	1294 (35.4)	3658 (100)
TBA	666 (65.9)	344 (34.1)	1010 (100)	9 (64.3)	5 (35.7)	14 (100)	675 (65.9)	349 (34.1)	1024 (100)
Home	972 (63.5)	558 (36.5)	1530 (100)	13 (52.0)	12 (48.0)	25 (100)	985 (63.3)	570 (36.7)	1555 (100)
Birth order									
First birth	617 (59.0)	429 (41.0)	1046 (100)	5 (33.3)	10 (66.7)	15 (100)	622 (58.6)	439 (41.4)	1061 (100)
Non-first birth	3363 (65.9)	1743 (34.1)	5106 (100)	29 (50.0)	29 (50.0)	58 (100)	3392 (65.7)	1772 (34.3)	5164 (100

Table 4.3a: **Background characteristics of children (continued)**

Variables	Alive Fully Immunised			Dead Fully Immunised			Total Fully Immunised		
	Yes n(%)	No n(%)	Total N(%)	Yes n(%)	No n(%)	Total N(%)	Yes n(%)	No n(%)	Total N(%)
Child's age									
12-23 months	857 (56.8)	652 (43.2)	1509 (100)	12 (27.3)	32 (72.7)	44 (100)	869 (56.0)	684 (44.0)	1553 (100)
24-35 months	947 (52.3)	863 (47.7)	1810 (100)	23 (74.2)	8 (25.8)	31 (100)	970 (52.7)	871 (47.3)	1841 (100)
36-47 months	1175 (72.4)	447 (27.6)	1622 (100)	9 (90.0)	1 (10.0)	10 (100)	1184 (72.6)	448 (27.4)	1632 (100)
48-59 months	1155 (77.6)	333 (22.4)	1488 (100)	6 (85.7)	1 (14.3)	7 (100)	1161 (77.7)	334 (22.3)	1495 (100)
60-72 months	1088 (85.4)	186 (14.6)	1274 (100)	1 (100)	0 (0.0)	1 (100)	1089 (85.4)	186 (14.6)	1275 (100)

Source: DHDSS & DHRC 2011

Table 4.3b: **Background characteristics of children caretakers/mothers**

Variables	Alive Fully Immunised			Dead Fully Immunised			Total Fully Immunised		
	Yes n(%)	No n(%)	Total N(%)	Yes n(%)	No n(%)	Total N(%)	Yes n(%)	No n(%)	Total N(%)
Caretaker's age									
< 18 years	27 (45.0)	33 (55.0)	60 (100)	0 (0.0)	1 (100)	1 (100)	27 (44.3)	34 (55.7)	61 (100)
18-29 years	1868 (61.9)	1149 (38.1)	3017 (100)	18 (47.4)	20 (52.6)	38 (100)	1886 (61.7)	1169 (38.3)	3055 (100)
30-39 years	1708 (68.7)	779 (31.3)	2487 (100)	14 (53.9)	12 (46.1)	26 (100)	1722 (68.5)	791 (31.5)	2513 (100)
40-49 years	566 (69.2)	252 (30.8)	818 (100)	7 (50.0)	7 (50.0)	14 (100)	573 (68.9)	259 (31.1)	832 (100)
50-59 years	84 (81.6)	19 (18.4)	103 (100)	2 (66.7)	1 (33.3)	3 (100)	86 (81.1)	20 (18.9)	106 (100)
60 + years	19 (70.4)	8 (29.6)	27 (100)	0 (0.0)	0 (0.0)	0 (0.0)	19 (70.4)	8 (29.6)	27 (100)
Marital status									
Single	842 (59.1)	582 (40.9)	1424 (100)	7 (43.8)	9 (56.2)	16 (100)	849 (59.0)	591 (41.0)	1440 (100)
Currently married	3199 (67.4)	1545 (32.6)	4744 (100)	29 (49.2)	29 (50.8)	59 (100)	3228 (67.2)	1575 (32.8)	4803 (100)
Formally married	105 (65.2)	56 (34.8)	161 (100)	2 (100)	0 (0.0)	2 (100)	107 (65.6)	56 (34.4)	163 (100)

Table 4.3b: Background characteristics of children caretakers/mothers (continued)

Variables	Alive Fully Immunised			Dead Fully Immunised			Total Fully Immunised		
	Yes n(%)	No n(%)	Total N(%)	Yes n(%)	No n(%)	Total N(%)	Yes n(%)	No n(%)	Total N(%)
Educational level									
No education	1409 (66.0)	727 (34.0)	2136 (100)	19 (54.3)	16 (45.7)	35 (100)	1428 (65.8)	743 (34.2)	2174 (100)
Primary	1072 (64.8)	582 (35.2)	1654 (100)	12 (52.2)	11 (47.8)	23 (100)	1084 (64.6)	593 (35.4)	1677 (100)
Secondary	1788 (65.8)	931 (34.2)	2719 (1000	10 (41.7)	14 (58.3)	24 (100)	1798 (65.6)	945 (34.4)	2743 (100)
Household Wealth index									
Poorest	1043 (71.1)	425 (28.9)	1468 (100)	14 (53.9)	12 (46.1)	26 (100)	1057 (70.8)	437 (29.2)	1494 (100)
Poorer	1052 (67.3)	511 (32.7)	1563 (100)	7 (46.7)	8 (53.3)	15 (100)	1059 (67.1)	519 (32.9)	1578 (100)
Poor	853 (66.5)	430 (33.5)	1283 (100)	14 (70.0)	6 (30.0)	20 (100)	867 (66.5)	436 (33.5)	1303 (100)
Less poor	827 (64.2)	461 (35.8)	1288 (100)	6 (46.2)	7 (53.8)	13 (100)	833 (64.0)	468 (36.0)	1301 (100)
Least poor	1054 (73.3)	383 (26.7)	1437 (100)	5 (71.4)	2 (28.6)	7 (100)	1059 (73.3)	385 (26.7)	1444 (100)

Table 4.3b: Background characteristics of children caretakers/mothers (continued)

Variables	Alive Fully Immunised			Dead Fully Immunised			Total Fully Immunised		
	Yes n(%)	No n(%)	Total N(%)	Yes n(%)	No n(%)	Total N(%)	Yes n(%)	No n(%)	Total N(%)
Occupation									
Not working	757 (63.8)	430 (36.2)	1187 (100)	14 (60.9)	9 (9.1)	23 (100)	771 (63.7)	439 (36.3)	1210 (100)
Farmer	1353 (68.4)	626 (31.6)	1979 (100)	11 (44.0)	14 (56.0)	25 (100)	1364 (68.1)	640 (31.9)	2004 (100)
Artisan	489 (70.6)	204 (29.4)	693 (100)	2 (50.0)	2 (50.0)	4 (100)	491 (70.4)	206 (29.6)	697 (100)
Trader	1208 (64.7)	658 (35.3)	1866 (100)	12 (48.0)	13 (52.0)	25 (100)	1220 (64.5)	671 (35.5)	1891 (100)
Civil servant	52 (67.5)	25 (32.5)	77 (100)	0 (0.0)	0 (0.0)	0 (0)	52 (67.5)	25 (32.5)	77 (100)
Students	264 (57.8)	193 (42.2)	457 (100)	2 (40.0)	3 (60.0)	5 (100)	266 (57.6)	196 (42.4)	462 (100)
Fisherman	56 (60.2)	37 (39.8)	93 (100)	0 (0.0)	0 (0.0)	0 (0)	56 (60.2)	37 (39.8)	93 (100)
Others	69 (57.0)	52 (43.0)	121 (100)	0 (0.0)	0 (0.0)	0 (0)	69 (57.0)	52 (43.0)	121 (100)

Source: DHDSS & DHRC 2011

4.4 Assessing the factors that influence child mortality

From Table 4.4a and 4.4b, the likelihood of being dying was higher for children who were partially immunised (OR=1.73, 95% CI=1.15, 2.61) compared with the reference group (fully immunised). After controlling for child's sex, child's age and household wealth index, the likelihood of partially immunised children was (OR=1.12, 95% CI=0.71-1.77) compared to fully immunised. Males children are 1.73 times more likely to die compared with females children. The likelihood of a child dying was higher in children delivered by TBA (Traditional Birth Attendant) (OR=1.43, 95% CI=1.01-2.84) and children delivered at home (OR=1.69, 95% CI=1.01-2.84) compared with the reference group (Children delivered at the Health facility). Children who were not the first live birth of their mothers' had 21% lower likelihood of dying (OR=0.79, 95% CI=0.45-1.40). There is a lower likelihood of older children aged 60-72 months (OR=0.03, 95% CI=0.00-0.20), 48-59 months (OR=0.16, 95% CI=0.07-0.36), 36-47 months (OR=0.21, 95% CI=0.11-0.42), 24-35 months (OR=0.59, 95% CI=0.37-0.93) dying compared with the reference group (aged 12-23 months). Caretakers/mothers with some level of education have lower likelihood of their children, Primary education (OR=0.84, 95% CI=0.50-1.44), Secondary education (OR=0.53, 95% CI=0.32-0.91) dying compared to Caretakers/mothers with no education. Household with higher wealth index also had a lower likelihood of their children, Poorer (OR=0.54, 95% CI=0.29-1.03), Poor (OR=0.88, 95% CI=0.49-1.58), Less poor (OR=0.56, 95% CI=0.29-1.11), Least poor (OR=0.27, 95% CI=0.12-0.63) dying compared with the reference group. Furthermore, mothers/caretakers who are working also had lower likelihood of their children Farmers (OR=0.65, 95% CI=0.37-1.15), Artisan (OR=0.29, 95% CI=0.10-0.86), Trader (OR=0.69, 95% CI=0.39-1.22), Students (OR=0.56, 95% CI=0.21-1.49) dying compared to mothers/caretakers not working.

Table 4.4a: Univariate analysis of risk factors associated with mortality among children aged 12-71 months in Dangme West District

	Unadjusted OR	Standard error	P-value	95% CI
Immunizations				
Fully immunised	1	-	-	-
Partially immunised	1.73	0.3636	0.009	(1.15 , 2.61)
Sex				
Female	1	-	-	-
Male	1.73	0.3776	0.012	(1.13 , 2.66)
Place of birth				
Health facility	1	-	-	-
TBA	1.43	0.4566	0.257	(0.76 , 2.68)
Home	1.69	0.4459	0.046	(1.01 , 2.84)
Birth order				
First birth	1	-	-	-
Non-first birth	0.79	0.2310	0.424	(0.45 , 1.40)
Child's age				
12-23 months	1	-	-	-
24-35 months	0.59	0.1392	0.025	(0.37 , 0.93)
36-47 months	0.21	0.0745	<0.001	(0.11 , 0.42)
48-59 months	0.16	0.0659	<0.001	(0.07 , 0.36)
60-72 months	0.03	0.0272	<0.001	(0.00 , 0.20)

Table 4.4a: Univariate analysis of risk factors associated with mortality among children aged 12-71 months in Dangme West District (continued)

	Unadjusted OR	Standard error	P-value	95% CI
Caretaker's age				
< 18 years	1	-	-	-
18-29 years	0.76	0.77	0.784	(0.10 , 5.60)
30-39 years	0.62	0.64	0.650	(0.08 , 4.70)
40-49 years	1.03	1.07	0.980	(0.13 , 7.94)
50-59 years	1.74	2.04	0.632	(0.17 , 17.18)
60 + years	-			
Caretaker's Marital status				
Single	1	-	-	-
Currently married	1.11	0.3138	0.720	(0.64 , 1.93)
Formally married	1.11	0.8342	0.894	(0.25 , 4.85)
Caretaker's Educational level				
No education	1	-	-	-
Primary	0.84	0.2295	0.544	(0.50 , 1.44)
Secondary	0.53	0.1436	0.020	(0.32 , 0.91)

Table 4.4a: Univariate analysis of risk factors associated with mortality among children aged 12-71 months in Dangme West District (continued)

	Unadjusted OR	Standard error	P-value	95% CI
Household Wealth index				
Poorest	1	-	-	-
Poorer	0.54	0.1768	0.060	(0.29 , 1.03)
Poor	0.88	0.2639	0.670	(0.49 , 1.58)
Less poor	0.56	0.1948	0.100	(0.29 , 1.11)
Least poor	0.27	0.1176	0.003	(0.12 , 0.63)
Caretaker's Occupation				
Not working	1	-	-	-
Farmer	0.65	0.1899	0.142	(0.37 , 1.15)
Artisan	0.29	0.1620	0.026	(0.10 , 0.86)
Trader	0.69	0.2014	0.205	(0.39 , 1.22)
Civil servant	-	-	-	-
Students	0.56	0.2803	0.250	(0.21 , 1.49)
Fisherman	-	-	-	-
Others	-	-	-	-

Source: DHDSS & DHRC 2011

Table 4.4b: Multivariate analysis of risk factors associated with mortality among children aged 12-71 months in Dangme West District

	Adjusted OR	Standard error	P-value	95% CI
Immunizations				
Fully immunised	1	-	-	-
Partially immunised	1.12	0.2600	0.619	(0.71 , 1.77)
Sex				
Female	1	-	-	-
Male	1.75	0.4116	0.016	(1.11 , 2.78)
Child's age				
12-23 months	1	-	-	-
24-35 months	0.60	0.1560	0.051	(0.36 , 1.00)
36-47 months	0.26	0.0956	<0.001	(0.13 , 0.54)
48-59 months	0.20	0.0855	<0.001	(0.09 , 0.46)
60-72 months	0.03	0.0350	0.001	(0.00 , 0.25)
Wealth index				
Poorest	1	-	-	-
Poorer	0.55	0.1809	0.070	(0.29 , 1.05)
Poor	0.91	0.2752	0.757	(0.50 , 1.64)
Less poor	0.55	0.1899	0.084	(0.28 , 1.08)
Least poor	0.27	0.1189	0.003	(0.12 , 0.64)

Source: DHDSS & DHRC 2011

CHAPTER FIVE

5.0 CONCLUSIONS AND RECOMMENDATIONS

We have described the factors that affect child mortality. We applied Logistic regression to determine the factors that affect child mortality in Dangme West District of Ghana. This chapter presents the conclusions and recommendations.

5.1 CONCLUSIONS

The data on child mortality and vaccination status in Dangme West District of Ghana gives strong support to the argument that effort to implement the Expanded Programme on Immunization has substantially enhance child survival. Parents or caregivers that do not complete their vaccinations (partially immunised) for their children have a higher likelihood (OR=1.73, 95% CI=1.15, 2.61) of their children dying compared with children who complete (fully immunised) their vaccinations. After controlling for sex of child, household wealth index and child's age, the likelihood of partially immunised child dying was (OR=1.12, 95% CI=0.71-1.77). The immunization coverage among children who were alive (67.8%) was higher than among children who were dead (54.8%).

Others have argued that such vaccination programs will eliminate only the proportion of mortality directly attributable to the targeted diseases (Foster 1995) or that they will have no net effect on all-cause mortality because weak children saved from vaccine-preventable diseases will die of other causes in health-deprived settings (Mosley and Chen 1984). Our data add to a growing body of evidence that suggests completing the full immunization for a child reduces child mortality significantly.

5.2 RECOMMENDATIONS

Dangme West district of Ghana is far from reaching MDG goal 4. For the district to be able to meet the MDG goal 4 by 2015, we recommend further research to be conducted across the country to find out why some children do not complete their vaccination and this will help the health policy planners know the exact strategy to use to sensitize the public. This will enable the programme planners put in appropriate strategies in order to achieve our universal coverage of 90% by 2015.

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