KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY, KUMASI

Using Binary Logistic and Quantile Regressions for Determinants of Preterm Birth in Ghana. Case Study; Ahafo Ano South District, Ashanti Region

By

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MASTER OF PHILOSOPHY

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Declaration

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

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Dedication

I wish to humbly dedicate this piece of work, first, to the Almighty God who by His mercies and blessings, granted me with strength and wisdom throughout this long academic journey.

Secondly, I express my sincere gratitude to my parents, Mr. and Mrs Yamoah, for their physical and spiritual guidance towards my entire formal education. Another appreciation also goes to two gallant mortals: Mr. John Berko and Mrs. Julliet Boamah for their advice and support.

Finally, I dedicate this work to Mr. and Mrs. Yamoah, who were with me throughout the turbulent moments. I say ”mo ne ye” to all of you.

Abstract

Using data obtained from the Biostatistics Unit at the Mankranso Government Hospital, this thesis examines the prevalence rate and determinant factors of preterm birth at the Ahafo Ano South District. Retrospective data on relevant variables of delivered mothers and the neonates were extracted from the database of the unit. The extracted data used in this hospital-based study spans from January 2012 to the first quarter of 2013. The study excluded still-birth or macerated babies from its analysis. The binary quantile and logistic regressions were employed to ascertain the causal factors of preterm birth and the associated causal effects. Out of the 711 live births, 336, representing 47.3% were born preterm; meaning approximately, every 4 out of 9 babies are born preterm in the district. From the binary logit regression, the study identified the baby's weight, the age of the delivered mother, intermittent preventive treatment and number of conceived fetuses, as significant determinant factors of preterm birth. In addition to these variables, the bivarite analysis included gravidity and parity. The Bayesian binary quantile regression at a lower quantile of $\tau = 0.05$ recorded significant varying effects for maternal age, APGAR score of the newly born at 5 minutes, antenatal, delivery type, parity and complication during the pregnancy cycle. However, at the median and upper-tail quantiles, no significant effects were recorded.

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Background of the study

In recent times, the prospects of many developing economies around the globe have been expressed through the young and energetic human resource structure of such economies. It is often believed that any economy whose labour force is denominated by young people is already on a wheel of seeing rapid economic development. What then has happened to most developing economies such as Ghana? According to report from the 2010 population and housing census, about 56.94% (14,040,893 out of 24,658,823) of Ghanaians are between the labour force age bracket of fifteen to sixty-four (Ghana Statistical Service, 2012), yet, the country-s economy keeps retrogressing. There might be several economic reasons for such retrogressing development, but for this study, attempts are made to focus on the principal actors of the economy. With or without natural resource deposits, the principal actors of every economy would be the natural workforce of that particular economy. This logically means any occurrences that threaten the general health or survival of such national workforce directly weakens the country's quest to develop fast. The future of Ghana's youth-driven human resource base, has long been faced with life threatening issues, hence, the country's move to adopt the Millennium Development Goals (MDG) 4 and 5. These goals seek to address issues covering the sustainability of the next generation of youth for the country. Moreover, relevant to this study, the MDG 4 was adopted by government to drastically reduce infant and child mortality by 2015. The question is, if increasingly, Ghana's infants and children are to die that early, who are those to form the country's future workforce? Your guess may be as good as mine: the country's economic workforce might then be well-dominated by the vulnerable aged. How then do we develop as a developing country?

In answering to these issues, government intervened and opted for the MDG 4 to help address the matter at hand. In doing so, the Government of Ghana has committed itself to channel resources in fighting infant and child mortality to the barest minimum, before the target year of 2015. This timely intervention might help sustain its youth-driven economy. However, according to the World Health Organization figures for 2010, Ghana's infant mortality remains relatively high as 50 deaths per 1000 live births, and that of child mortality stood at 74 deaths per 1000 live births (WHO, 2012). Comparatively, the infant mortality rates of countries such as Botswana (36 deaths per 1000 live births), Cape Verde (29 deaths per 1000 live births) and Belgium (4 deaths per 1000 live births) propel a negative signal to the efforts being made by Ghana. These recorded figures trigger alarming concerns with obvious indication that, Ghana is a little far behind achieving its 2015 target. What then could have been the key causes of infant/child morbidity and mortality in the country? Several studies (WHO, 2007A; WHO, 2007b; Afable-Munsuz and Braveman, 2008; Kasa, et al., 2012) have identified low birth weight, preterm birth, malnutrition, unplanned pregnancy, unsafe/unsuccessful abortion and alcoholism by pregnant women as the most dominated causes of neonate, infant and child mortality. Addressing these causes have been pin-pointed by these studies as the main antidote to curbing the increasingly rate of neonate, infant and child mortality around the length and breadth of the globe.

With emphasis on the Ghanaian perspective, not much on the causes of neonatal-, infant- and child-mortality have been given prioritized scientific investigation. However, according to a report by the Ministry of Health (2007), as at the end of 2006, under-five (5) mortality in Ghana remained considerably high as, 111 deaths per 1000 live births. The report further revealed that, newborn deaths (ie., between birth and 28 days of life) composited an important component of child mortality in Ghana, representing 40% of all deaths (43 deaths per 1000 live births) in 2003. Moreover, it was estimated that 40% of all neonatal deaths occurred in the first 24 hours, and 75% in the first 7 days of life. Meanwhile, the report aligned prematurity (preterm birth), low birth weight, infections and asphyxia as primary causes of these recorded mortalities, yet, in a sharp contrast, it recounted that majority of infants or child deaths in Ghana are caused by conditions that are preventable or treatable with simple and low-cost interventions. What then could be these causal conditions? Knowing such causal factors might easily help to implement interventions or remedies that would be used to drastically reduce these unfortunate but preventable mortalities. In finding scientific answers to this question, this current study focuses its attention to basically investigate into the prevalence rate, and the determinant factors of prematurity (or preterm birth); one of the primarily associated factors of infant and child mortality, in an administrative district part of Ghana. Preterm birth has been identified to be a root cause of infant/child morbidity and mortality, but less is scientifically known of its determinant factors under the Ghanaian context. Aside being a cause of infant and child mortality, it is documented to also inflict several diseases such as impairments, cerebral palsy, disabilities and lungs related complications in the adult life of infants who luckily survived being born preterm (Best Start, 2002). These adverse health effects of preterm birth on the national workforce of the country need to be of disturbing concern to all stakeholders. A country which needs to develop must seek, holistically, the general health concerns of its workforce. It is in line with this keynote that this study moves to assess the prevalence rate and determinant factors of preterm birth in parts of Ghana. Seeking to expose these determinant factors might be the first most important step to addressing the issue, and also to achieve the MDG 4 target, which is never too late from now.

1.2 The Problem Statement

Per the significant contribution of prematurity to morbidity and mortality, WHO, in collaboration with other world organizations, presented a new goal in 2010 to reduce mortality due to preterm birth by 50% between 2010 and 2025.

However, prematurity is estimated as the leading cause of mortality in the country for the first month of life in Ghana, ranking the country on 25th position in the world (UNICEF, 2013).

This recent occurrences has necessitated immediate scientific research to examine determinant factors of prematurity or preterm birth in the country.

1.3 Objectives of the Study

The objectives of this study are:

1. To assess the prevalence rate of preterm births among delivered mothers at the Ahafo Ano South District;
2. To examine determinant factors that significantly contribute to incidence of preterm births at the district using binary quantile and logistic regressions;
3. To ascertain the rate at which pregnant mothers enroll to patronize antenatal services at the district.

1.4 Research Questions

To mainly achieve the set objectives of this study, and to continually stay focused throughout the study period, the following research questions were formulated:

1. How frequent are cases pertaining to preterm births recorded?

2. What determinant factor(s) contribute to preterm births among pregnant women?

3. What fraction or proportion of the delivered mothers attended antenatal proceedings?

1.5 Research Design/Methodology

The data used in this study was obtained from the Biostatistics Unit at Mankranso Government Hospital. The extracted data obtained from the hospital covers records of pregnant women who accessed maternity services from January 2012 up to the first quarter of 2013. This hospital-based study extracted key variables on pregnant/delivered women, as well as their respective neonates. The study then employed the binary quantile and logistic regressions to obtain determinant factors of neonates who were entirely born preterm under the study period.

1.6 Significance of the Study

Generally, the backbone of any strong economy is seen through its human resource base. Most often, the chunk of such human resource comprises of the energetic young men and women in those economies. This reasonably portrays that, any event or occurrence that undermines the entire health or the survival of young people in any economy should be of alarming concern to policy makers and all other stakeholders. Preterm birth is one of such occurrences that has gained global attention as a major contributor to infant/child morbidity and mortality. As mentioned already in sub-section 1.1, babies or neonates born preterm are documented in literature to often have less likelihood to survive, and even those who survive sometimes record adverse health conditions in their adult lives. In pursuance to these adverse effects caused by preterm birth in many developing countries such as Ghana, this study is in order to inform stakeholders of the prevalence rate of the situation in parts of the country. From the observed prevalence rate of preterm birth in parts of the country, the study would serve as a base to asses Ghana's ability to achieve the Millennium Development Goal of reducing infant/child mortality, since preterm birth is one of the major causes of this kind of mortality.

Moreover, the study dives into the situation to expose determinant factors that contribute to the occurrences of the recorded preterm cases in the study area. Making known the causes of preterm birth to the general populace, and to policy makers may to a greater extent increase its awareness and thereby reduce the rate of occurrences. This may directly help the country to build a stronger and healthier human-resource base, coupled with energetic future young men and women.

1.7 Limitations of the Study

A study to generally assess determinant factors of preterm births in developing countries such as Ghana should cover a wide range of major maternity facilities within the length and breadth of the country. This study could not do so due to the following constraints:

1. Several visited maternity facilities do not keep appropriate historical records of patients who accessed such facilities;
2. Facilities which claimed to have appropriate historical records could either not locate the records in their archives or did locate the records, but they were partly consumed by rodents due to the manual storage of the records;
3. Relatively, the few facilities which had proper computerized data system (database) do not record enough relevant variables on patients who access their maternity services;
4. Facilities with enough databases covering their maternity services do not collect

uniform variables across-board. This makes it difficult to undertake any appropriate joint study involving all maternity facilities. There exists no central pool of data covering entire records of preterm births in the country.

With these identified constraints, we were handicapped to include other maternity facilities, apart from the only mentioned maternity facility in the earlier sections (Mankranso Government Hospital).

1.8 Organization of the Study

The subsequent four chapters of the study were structured as follows:

Chapter 2 reviews preterm birth as a major public health concern across the globe. The chapter again reviews previous research works on the prevalence rate, determinant factors, and consequences of preterm births in several multi-country studies.

Chapter 3 initially gives brief description of the study area. It also present detailed explanation of the two main statistical techniques used in the study: binary quantile and logistic regressions.

Chapter 4 thoroughly presents various results and analyses of major findings from the study. The last chapter generally introduces readers to summary of key findings, and also recommends remedies based on such findings.

Chapter 2

Literature Review

2.1 Introduction

The Chapter basically reviews contemporary background of preterm birth, as its gains prominence in global health outcry. It again reviews previous research works on key determinant factors of preterm births, consequences, and remediation practices or interventions geared towards controlling preterm births in several multi-country studies. The Chapter finally concludes with recaps of salient points from the review.

2.2 Preterm Birth: Why is it a Major Health Concern?

Prematurity or preterm birth has been widely and acceptably defined to include babies born alive before 37 weeks of pregnancy are fully completed. There are several subcategories of preterm birth based on weeks of gestational age. These include, extremely preterm (< 28 weeks), very preterm (28 to < 32 weeks) and moderate to late preterm (32 to < 37 weeks). From a March of Dimes (2011) report, of the nearly 30,000 babies who die each year before their first birthday, 68% are born preterm, and more than half a million babies are born premature in the United States (US); meaning, 1 in every 8 births result to preterm birth in US. The March of Dimes report continually stresses that, preterm infants (< 37 weeks) are 15 times as likely to die as full-term babies during the first year of life, and very premature infants (28 to < 32 weeks) are 73 times as likely to die during this same period. Report from a Best Start (2002) document, gives an indication that, 8% of babies, or 1 in 12 babies are overly born preterm in Ontario.

According to a global action report on preterm birth, compiled by March of Dimes, PMNCH, Save the Children and WHO (2012), an overwhelming estimated 15 million babies are born too soon (or premature) every year. This means, more than 1 in 10 babies are born preterm, affecting families all around the world. Based on reliable data from the report, preterm birth rates are mostly increasing in almost all countries across the globe. However, out of the estimated 15 million preterm birth cases worldwide, 60% of the entire cases occur in Sub-Saharan Africa and in South Asia. Over 90% of extremely preterm babies (< 28 weeks) born in these areas die within the first few days of life. On the average, 12% of babies born too soon (preterm born babies) are from the world's poorest countries, and 9% of cases pertaining to preterm birth are found in higher-income countries. The prevalence rate of preterm birth ranges from 5% to 18% across 184 countries of the world, and more than 80% of such cases occur between 32 - 37 weeks of gestation. The report by March of Dimes, PMNCH and WHO (2012), further attest that, over 1 million children die each year due to complications of preterm birth. The estimated high mortality rate due to complications of preterm birth was reaffirmed in a study by Lawn, et al., (2005), in which the authors described preterm born babies to have accounted for 27% of nearly 4 million neonatal deaths worldwide every year. This has made prematurity the leading cause of newborn deaths (babies in the first 4 weeks of life), and now, the second leading cause of death after pneumonia in children under the age of five (5). It was also documented from the report of these three internationally acclaimed organizations that, many preterm survivors face a lifetime of disability, including hearing and visual disabilities or challenges. In accelerating preventive remedies for preterm birth, the report outlined among several interventions which included effective family planning and continual increases in the empowerment of women, especially adolescents, plus improved quality of care before, between and during pregnancy; and strategic investments in innovation and research. Their report additionally opted for urgent action to be undertaken to address the estimated 15 million babies born too soon, especially, as they articulate preterm birth rates to be increasing each year. They expressed such action as essentially needed, in order to progress on the Millennium Development Goal (MDG) for child survival by 2015 and beyond, since they claimed 40% of under-five deaths are in newborns; and also recounted that such action will give added value to maternal health (MDG 5) investments.

In a study by Beck et al., (2009), the authors analyzed preterm birth rates worldwide; to generally assess the incidence of this public health problem, map the regional distribution of preterm births and to gain insight into existing assessment strategies. The authors extracted worldwide data on preterm birth rates during a previous systematic review of published and unpublished data on maternal mortality and morbidity reported between 1997 and 2002. Those data were supplemented through a complementary search covering the period 2003-2007. Region-specific multiple regression models were used to estimate the preterm birth rates for countries with no data. From their findings, it was estimated that in 2005, 12.9 million births, or 9.6% of all births worldwide, were preterm. Approximately 11 million (85%) of these preterm births were concentrated in Africa and Asia, while about 0.5 million occurred in each of Europe and North America (excluding Mexico) and 0.9 million in Latin America and the Caribbean. The highest rates of preterm birth were much concentrated in Africa and North America (11.9% and 10.6% of all births, respectively), and the lowest were recorded in Europe (6.2%). In their conclusion remarks, Beck et al., (2009) single-out preterm birth as an important significant perinatal health problem across the globe. Additionally, the authors revealed that, developing countries, especially those in Africa and South Asia, incurred the highest burden in terms of absolute numbers, although a high rate was also observed in North America. They however cautioned that, a better understanding of the causes of preterm birth and improved estimates of the incidence of preterm birth at each country's level, are needed to improve access to effective obstetric and neonatal care.

To a more current study, Chang et al., (2012) examined trends and estimated the potential reduction in preterm births for countries with very high human development index (VHHDI) if present evidence-based interventions were widely implemented. Their analysis was carried out to mainly inform a rate reduction target for Born Too Soon (or preterm birth cases). Countries were assessed for inclusion, based on availability and quality of preterm prevalence data (2000-2010), and trend analyses with projections were undertaken. Chang and his research team also analyzed drivers of preterm birth rate increases in the USA, for the period spanning from 1989-2004. For 39 countries with very high human development index (VHHDI) and with more than 10,000 births, the authors did country-by-country analyses based on target population, incremental coverage increase, and intervention efficacy. From 2010, even if all countries with VHHDI achieved annual preterm birth rate reductions of the best performers for 1990-2010 (Estonia and Croatia), 2000-2010 (Sweden and Netherlands), or 2005-2010 (Lithuania, Estonia), rates would experience a relative reduction of less than 5% by 2015 on average, across the 39 selected countries. For their analysis, the preterm birth rise from 1989-2004 in USA suggests half the change is unexplained, but important drivers include non-medically indicated labour induction and caesarean delivery and assisted reproductive technologies. For all 39 countries with VHHDI, five interventions modeling at high coverage predicted a 5% relative reduction of preterm birth rate from 9.59% to 9.07% of live births: smoking cessation (0.01 rate reduction), decreasing multiple embryo transfers during assisted reproductive technologies (0.06), cervical cerclage (0.15), progesterone supplementation (0.01), and reduction of non-medically indicated labour induction or caesarean delivery (0.29). These findings translate to roughly 58,000 preterm births averted, and total annual economic cost savings of about US$3 billion. The authors recommended a conservative target of a relative reduction in preterm birth rates of 5% by 2015.

They again highlighted the urgent need for research into underlying mechanisms of preterm births, and development of innovative interventions. Furthermore, they iterated that, the highest preterm birth rates occurred in low-income settings where the causes of prematurity might differ and have simpler solutions such as birth spacing and treatment of infections in pregnancy than in high-income countries. This means, urgent focus on these settings is much crucial to reducing preterm births worldwide.

In 2004, 12.5% of births in the United States were preterm. This rate has increased steadily in the past decade. There are significant, persistent, and very troubling racial, ethnic, and socioeconomic disparities in the rates of preterm birth in the US. The highest rates are for non-Hispanic African Americans, and the lowest are for Asians or Pacific Islanders. In 2003, the rate of preterm birth for African-American women was 17.8%, whereas the rates were 10.5% for Asian and Pacific Islander women and 11.5% for white women. Infants born preterm are at greater risk than infants born at term for mortality and a variety of health and developmental problems. Preterm birth complications include acute respiratory, gastrointestinal, immunologic, central nervous system, hearing, and vision problems, as well as longer-term motor, cognitive, visual, hearing, behavioral, social-emotional, health, and growth problems. The birth of a preterm infant can also bring considerable emotional and economic costs to families and have implications for public-sector services, such as health insurance, educational, and other social support systems. The annual societal economic burden associated with preterm birth in the United States was at least $26.2 billion in 2005. However, the current methods for the diagnosis and treatment of preterm labour are currently based on an inadequate literature, and little is known about how preterm birth can be prevented. Treatment has been focused on inhibiting contractions. This has not reduced the incidence of preterm birth but has delayed delivery long enough to allow the administration of antenatal steroids and transfer of the mother and fetus to a hospital where they may receive appropriate care. These interventions have reduced the rates of perinatal mortality and morbidity. Although improvements in perinatal and neonatal care have significantly improved the rates of survival for infants born preterm, these infants remain at risk for a host of acute and chronic health problems. This suggests that, therapies and interventions for the prediction and the prevention of preterm birth are urgently needed. Upon review of the literature assessing the causes and consequences of preterm birth, the diagnosis and treatment of women at risk for preterm labor, and treatments for infants born preterm, this report proposes a research agenda for investigating the problem of preterm birth that is intended to help focus and direct research efforts. Priority areas are: (1) the establishment of multidisciplinary research centers; (2) improved research in three areas including better definition of the problem of preterm birth with improved data, clinical and health services research investigations, and etiologic (study of causes) and epidemiologic investigations; and (3) the study and informing of public policy (Behrman and Butler, 2007).

The enormous complications or consequences of preterm birth cannot be easily collated and quantified in one single study. However, a current work by Moreira et al., (2013), in a study on effect of preterm birth, examined and synthesized available knowledge in literature about the effects of preterm birth on motor development, behavior, and the school performance of school-age children. The authors work was based on a systematic review of studies published in the past ten years, and indexed in databases such as, MEDLINE/Pubmed, MEDLINE/BVS; LILACS/BVS; IBECS/BVS; Cochrane/BVS, CINAHL, Web of Science, Scopus, and PsycNET in three languages (Portuguese, Spanish, and English). Observational and experimental studies that assessed motor development and/or behaviour and/or academic performance and those whose target-population consisted of preterm children, aged 8 to 10 years were included. Article quality was assessed by strengthening the reporting of observational studies in epidemiology (STROBE) and Physiotherapy Evidence Database (PEDro) scales; articles that did not achieve a score of 80% or more were excluded. From their findings, the electronic search identified 3,153 articles, of which 33 were included based on the eligibility criteria. Only four studies found no effect of prematurity on the outcomes (two articles on behaviour, one on motor performance and one on academic performance). Among the outcomes of interest, behaviour was the most searched (20 articles, 61%), followed by academic performance (16 articles, 48%) and motor impairment (11 articles, 33%). In their conclusion, the authors outlined that, premature infants are more susceptible to motor development, behaviour and academic performance impairment when compared to term infants. They moreover recommended that such types of impairments, whose effects are manifested in the long term, can be prevented through early parental guidance, monitoring by specialized professionals, and interventions.

According to Best Start (2002), preterm birth or delivery does not only pose challenges to the newborn alone. It widely affects the family of the preterm born baby by causing emotional distress through uncertainty of the baby's future; the community (via resources to assist such babies in achieving optimal quality of life); and on the healthcare system of a country through provision of neonatal intensive care unit and modern medical equipment such as incubators, etc. The report again stresses that preterm babies are much exposed to adverse health challenges such as immature lungs, infections, intra-cerebral haemorrhage, Sudden Infant Death Syndrome (SIDS), emotional or physical disabilities and patent ductus arteriosis (heart problem involving the inability of the duct to close). Johnson (2007) also identified preterm born babies to be associated with poor cognitive abilities. To a more current situation, Molnár and Rutherford (2013), examined brain maturation after preterm birth in two translational studies-one in humans and one in sheep. The authors were of the view that premature birth was associated with delayed maturation of grey matter in the cerebral cortex. However, they recommended medical care that prohibits impairment of growth in premature neonates to enhance cortical development and thereby reducing neurological disabilities associated with preterm birth.

In addition to its significant contribution to mortality, the effect of preterm birth amongst some survivors may continue throughout life, impairing neuro-developmental functioning through increasing the risk of cerebral palsy, learning impairment and visual disorders and affecting long-term physical health with a higher risk of non-communicable disease (Rogers and Velten, 2011).

From a document compiled by European Lung Foundation (2010), babies who survive being born preterm have potential threat of contracting lung related problems such as Bronchopulmonary Dysplasia (BPD), Respirator Distress Syndrome (RDS) and Respirator Syncytial Virus (RSV) in their childhood or adult life. Black et al., (2012), also established prematurity to have had negative effects on nephrogenesis development in the process of developing the kidney of the fetus. In 2005, preterm births in the United State alone cost the country more than $26 billion for expenses on medical, delivery, early intensive services, special education and lost productivity. The cost of saving a life of very low weight preterm newborn was estimated at $550, 000 (March of Dimes, 2011).

Due to the significant contribution of prematurity to morbidity and mortality, four well-acclaimed international bodies: March of Dimes, Partnership for Maternal, Newborn and Child Health (PMNCH), Save the Children, and World Health Organization (WHO), in 2010 presented a new goal for the reduction of deaths due to complications of preterm birth. They stated in the set goal that: for countries with a current neonatal rate level of more than or equal to 5 per 1,000 live births, the goal is to reduce the mortality due to preterm birth by 50% between 2010 and 2025; and for countries with a current neonatal mortality rate level of less than 5 per 1,000 live births, the goal is to eliminate remaining preventable preterm deaths, focusing on equitable care for all, and quality of care to minimize long-term impairment. Their collective efforts would supplement the MDG 4 target of drastically reducing infant and child mortality by 2015.

The current section has successfully reviewed contemporary background of preterm birth, as viewed as a recent most single largest direct cause of neonatal deaths, and second most common cause of under - 5 mortality across the globe after the pneumonia pandemics. It primarily reviewed the world's prematurity prevalence rates, the most vulnerable people or group of persons in certain geographical areas, challenges or consequences, and preventive or remediation practices of preterm delivery. The next section generally reviews literature on causal factors of preterm birth, as documented in multi-country studies (thus, low- and high-income countries) all over the world.

2.3 Previous Research Works on Preterm Birth

Under this subsection, we generally reviewed previous multi-country research articles on preterm birth. From the reviewed works, we reported the issues being investigated; the methodology employed; and key findings or conclusions made. In several of such works, we made known of determinant factors of preterm births, previously identified by researchers around the globe. The kind association or the extents of effects that the identified factors exert on preterm delivery or birth were also reported in some of the reviewed articles. For the purposes of gaining a clearer picture of the situation at hand, the reviewed works were classified into developed (high-income) and under-developed or developing (low-income) multi-country studies. This was done to generally allow readers appreciate the differences in occurrences, as well as determinant factors associated with preterm birth in the developed world, compared to situations in most developing countries. From the identified factors, the reviewed works also sought to ascertain biological, socio-demographical, obstetric/previous delivery history, epidemiological, clinical, psychosocial characteristics and any other set of factors peculiar to preterm birth cases around the globe.

2.3.1 Dynamics of Preterm Birth in Developed Countries

The incidence rates of preterm deliveries in developed economies are far much different from happenings in under-developed or developing countries. It is reported that out of the world's annually estimated 15 million preterm birth cases, only 8.6% of such recorded cases basically occurs in well-advanced or developed countries such as Europe, United State, etc., as compared to the 60% recorded cases in just two developing continents: Sub-Saharan Africa and South Asia. With respect to the differences in the occurrence rates, this current subsection attempted to ascertain whether identified causes of preterm births in studies conducted within developed countries, or countries with much higher human development index, are also different from that of the developing countries. If such differences exist, policy interventions geared towards curtailing the preterm menace could be implemented bearing in mind the settings or background of the areas for which preterm births needs to be drastically reduced.

In finding determinant factors of preterm birth, Dole et al., (2002), in a work titled "Maternal Stress and Preterm Birth", identified a subset of multiple psychosocial factors on a large population of women, to have had varying effects on preterm birth. In their work, they examined a comprehensive array of psychosocial factors, including life events, social support, depression, pregnancy-related anxiety, perceived discrimination, and neighborhood safety in relation to preterm birth (<37 weeks) in a prospective cohort study of 1,962 pregnant women in central North Carolina, between 1996 and 2000, in which 12% delivered preterm. From the study's results, they recorded an increased risk of preterm birth among women with high counts of pregnancy-related anxiety (risk ratio (RR) = 2.1, 95% confidence interval (CI): 1.5, 3.0), with life events to which the respondent assigned a negative impact weight (RR = 1.8, 95% CI: 1.2, 2.7), and with a perception of racial discrimination (RR = 1.4, 95% CI: 1.0, 2.0). However, it was realized from the results that, different levels of social support or depression were not associated with preterm birth. They also found out that, preterm birth initiated by labour or ruptured membranes was associated with pregnancy-related anxiety among women assigning a high level of negative impact weights (RR = 3.0, 95% CI: 1.7, 5.3). Meanwhile, the association between high levels of pregnancy-related anxiety and preterm birth was reduced when restricted to women without medical co-morbidities, but they still choose to maintain such association in their analysis.

In consonance with the results published by Dole et al., (2002), Ifeoma et al., (2012), made known that, pregnant mothers exposed to high levels of psychological or social stresses, or better still severe life events are at increased risk of preterm birth. In the hospital-based study (conducted at Cork University Maternity Hospital, Ireland), Ifeoma et al., (2012) further identified clinical determinant factors of preterm birth. They explicitly found clinical depression, possibly due to its associated increase in smoking, alcohol and drug use, as a key player that increases the risk of preterm birth. It was also found from their work that, tobacco use alone increases the preterm birth rate by almost two (2) fold, due to the associated increased risk of small for gestational age and placental abruption. They again outlined that, approximately, 30-35% of preterm births are medically indicated, or iatrogenic due to medical or obstetric complications, while 40-45% are related to spontaneous preterm labour, and 25-30% are attributed to preterm pre-labour rupture of membranes (PPROM).

Severe alcohol consumption by pregnant mothers has also been linked with preterm deliveries in most developed countries. Prenatal alcohol consumption or exposure has been shown by studies (Burd et al., 2007; O'leary et al., 2009) to be significantly associated with preterm birth. In finding empirical answers to the research titled "Does alcohol increase the risk of preterm delivery?", Kesmodel et al., (2000), established that, consumption of 10 or more alcoholic drinks per week during the prenatal period, was associated with a nearly three (3) fold increase in the risk of preterm delivery. In another line of study, Bailey and Sokol (2011) admitted clearly that, alcohol consumption during pregnancy has wide-reaching effects on delivery outcomes such as miscarriage, stillbirth, preterm delivery and sudden infant death syndrome. Moreover, they appealed to health care providers to use reliable screening tools to help reduce the incidence and consequence of the preventable adverse effects that are attributable to drinking during pregnancy.

According to Joseph et al., (1998), for the past two decades, the rates of preterm birth have increased in many countries including Canada. However, they ascribed the factors contributing to the increasing cases of preterm birth as poorly understood. To made known the determinants of preterm birth rates in Canada, Joseph et al., (1998) used data from the Statistics Canada live-birth and stillbirth data bases to establish the effects of changes in the frequency of multiple births, registration of births occurring very early in gestation, patterns of obstetrical intervention, and the use of ultrasonographic dating of gestational age on the rates of preterm birth in Canada from 1981 through 1983 and from 1992 through 1994. All births in 9 of the 12 provinces and territories of Canada were included. Their study employed the Logistic and Poisson regression analyses to estimate changes between the two three-year periods, after adjustment for the above-mentioned determinants of the likelihood of preterm births. From the study's results, it was revealed that preterm births increased from 6.3 percent of live births in 1981 through 1983 to 6.8 percent in 1992 through 1994, a relative increase of 9 percent (95 percent confidence interval, 7 to 10 percent). Among singleton births, preterm births increased by 5 percent (95 percent confidence interval, 3 to 6 percent). Multiple births increased from 1.9 percent to 2.1 percent of all live births; the rates of preterm birth among live births resulting from multiple gestations increased by 25 percent (95 percent confidence interval, 21 to 28 percent). Adjustment for the determinants of the likelihood of preterm birth reduced the increase in the rate of preterm birth to 3 percent among all live births and 1 percent among singleton births. They further aligned that, the recent increase in preterm births in Canada was largely attributable to changes in the frequency of multiple births, obstetrical intervention, and the use of ultrasound-based estimates of gestational age.

Preterm birth complicates 12.5% of all deliveries in the USA, and remains the leading cause of perinatal mortality and morbidity, accounting for as many as 75% of perinatal deaths. Despite the recent temporal increase in preterm birth, efforts to understand the problem of prematurity have met with little success. This may be attributable to the under-appreciation of the etiologic (study of causes) heterogeneity of preterm birth as well as the heterogeneity in its underlying clinical presentations-spontaneous onset of labor, preterm premature rupture of membranes, and medically indicated preterm birth. With respect these unfortunate situation, Ananth and Vintzileos (2006), in a paper, reviewed data regarding preterm births with particular focus on its incidence, temporal causality trends, and recurrence. From their review, it was made clear that several studies pertaining to births from the USA gives general indication that, the recent temporal increase in the overall preterm birth rate is driven by an impressive concomitant increase in iatrogenic or medically indicated preterm birth. However, the largest temporal decline in perinatal mortality was reported to have also occurred among medically indicated preterm births (relative to other clinical subtypes), suggesting that these obstetric interventions at preterm gestational ages are associated with a reduction in perinatal mortality. They continued by making it known from their gathered recent data that, spontaneous preterm birth is not only associated with increased recurrence of spontaneous, but also medically indicated, preterm birth, and vice versa; meaning, clinical subtypes may share common underlying etiologies (study of causes). Since medically indicated preterm birth accounts for as many as 40% of all preterm births, efforts to understand the reasons for such interventions and their impact on short- and long-term morbidity in newborns is compelling. Ananth and Vintzileos (2006) suggested for another research to be conducted in order to meaningfully understand the mechanisms and etiology of preterm birth, thus leading to the possibility of effective preventive or therapeutic strategies.

To another related study conducted in the U.S.A, Stewart and Graham (2010) gave an overview of risk factors associated with preterm birth, and further suggested obstetrical management practices to control the increasing rate of preterm birth. For their study, they identified the history of preterm birth, short cervix, infection, short inter-pregnancy interval, smoking, and mothers whose lineage are traced to the African-American race, as significant factors to preterm deliveries. From their findings, the use of progesterone therapy to treat mothers at risk for preterm delivery was becoming more widespread. However, they discounted that the use of Tocolytics may not prevent preterm birth but have a role in prolonging pregnancy for administration of medications to benefit the preterm infant. These obstetric management practices include the use of antenatal steroids and, if indicated, magnesium sulfate for neuro-protection and intravenous antibiotics for Group B Streptococcus prophylaxis. Moreover, in finding antidotes to this adverse public health situation, Sosa et al., (2004) attempted to verify as to whether bed rest at home or in the hospital could help prevent the incidence of preterm birth cases in pregnant women who were designated to be at high risk for delivering preterm. They sampled articles from the Cochrane Pregnancy and Childbirth Group's Trials Register (July 2003), the Cochrane Central Register of Controlled Trials (The Cochrane Library, Issue 2, 2003), MEDLINE (July 2003), LILACS (July 2003), EMBASE (July 2003), POPLINE (July 2003) and bibliographies of relevant papers. The selection for inclusion of a paper was based on randomized and quasi-randomized controlled trials with reported data that assess clinical outcomes in women at high risk of spontaneous preterm birth who were prescribed bed rest in hospital or at home for preventing preterm birth, and their babies. One study met the inclusion criteria (1266 women), but the trials used for the selection was stated to have had uncertain methodological quality due to lack of reporting. In the selected paper, four hundred and thirty-two women (432) were prescribed bed rest at home and a total of 834 women received a placebo or no intervention. Sosa et al., (2004) then revealed from their search that, preterm birth (before 37 weeks) was similar in both groups (7.9% in the intervention group versus 8.5% in the control group), and the relative risk was 0.92 with a 95% confidence interval from 0.62 to 1.37. The authors therefore concluded that there is no evidence, either supporting or refuting the use of bed rest at home or in hospital, to prevent preterm birth. They cautioned clinicians not routinely advise women to rest in bed to prevent preterm birth due to its potential adverse effects. Moreover, not quite sure of the reliability from their findings, Sosa et al., (2004) suggested for additional future trials to evaluate both the effectiveness of bed rest, and the effectiveness of the prescription of bed rest, to prevent preterm birth.

Byron (2012), in a briefing paper on abortion and preterm birth, helped shed light on the cause of preterm birth by examining a disconcerting phenomenon, that is, that many medical papers appearing in peer reviewed journals have failed to mention their most important results: the link between preterm births and abortion. Byron's briefing paper demonstrates how such an important medical fact is being underreported, giving examples from the abundant literature showing how abortion increases the risk of preterm birth, most notably, an important 2011 Chinese study (by Liao et al.,). Byron argued that selective reporting of results in medical journals reflects the tendency of the medical community to disregard data showing an increased risk of preterm birth after an abortion, yet, the author did not only draw conclusion from the Liao et al., (2011) paper but from 127 other published studies demonstrating a statistically significant risk of preterm birth after an abortion. Results from Byron's brief review demonstrated overwhelming evidence to support the association of preterm birth with abortion prior to the incident pregnancy. For example, Byron reported an increased risk of preterm birth of 95 percent no matter when the abortion occurred in the patient's reproductive life, from a paper by Di-Renzo et al., (2011). In another reviewed paper in the work of Byron (2012), Lioa et al., (2011) were reported to have highlighted on the problems in interpreting abortion and preterm birth literature. For this latter paper, Byron vehemently criticized the authors for simply burying the most important clinical and statistical findings in the paper about medical abortions. Byron attacked the authors of merely reporting bias that pervades the study of abortion and preterm birth. Byron further described the continued efforts to deny the significant risk of preterm birth after only a single abortion are dishonest, disingenuous, and disrespectful, and outlined that, such efforts have, and will become even less effective as more women who experience preterm birth after an abortion begin to come forward. In a conclusion remarks, Byron therefore advised each country's department or ministry of health to fashion policies that will ensure proper information on the significant risks of abortion, and to decrease abortion rates.

Elsewhere at King's College Hospital in the United Kingdom, Beta et al., (2011) developed a model for prediction of spontaneous preterm delivery (before 34 weeks) based on maternal factors, placental perfusion and function at 11-13 weeks' gestation. Two groups of studies were considered: first, screening study of maternal characteristics, serum pregnancy-associated plasma protein-A (PAPP-A), free β-human chorionic gonadotrophin (β-hCG) and uterine artery pulsatility index (PI); second, case-control studies of maternal serum or plasma concentration of placental growth factor (PlGF), placental protein 13 (PP13), a disintegrin and metalloprotease 12 (ADAM12), inhibin-A and activin-A. The authors employed regression analysis to develop a model for the prediction of spontaneous early or preterm delivery. The authors revealed that, spontaneous early delivery occurred in 365 (1.1%) of the 34,025 pregnancies. A model based on maternal factors could detect 38.2% of the preterm deliveries in women with previous pregnancies at or beyond 16 weeks and 18.4% in those without, at a false positive rate (FPR) of 10%. In the preterm delivery group, compared with unaffected pregnancies, there were no significant differences in the markers of placental perfusion or function, except for PAPP-A which was reduced. They however concluded from their study's findings that, patient-specific risk of preterm delivery is provided by maternal factors and obstetric history. Moreover, they ascribed that, placental perfusion and function at 11-13 weeks were not altered in pregnancies resulting in spontaneous early delivery.

From an empirical review of selected articles, McAvoy et al., (2006) reported a set of aetiological determinants of preterm birth from one of the works (conducted by Kramer et al., 2000) in a developed country in which 25% of the women smoked during pregnancy, and a substantial minority were non-white. Based on the review, the authors identified low maternal body mass index, pregnancy-induced hypertension (PIH), multiple birth, genitor-urinary infection in pregnancy, incompetence cervix, cigarette smoking, cocaine, abruption placentae and prior previous preterm birth, as contributing factors to preterm delivery. From another selected article, McAvoy et al., (2006) re-iterated teenage pregnancies to be closely associated with prematurity, and that, preterm delivery rate of such teenagers far exceeded matched controls of women aged 20 - 24 years, in an Iris maternity hospital. It was again realized from several of the reviewed articles that, the risk of preterm birth increases among younger maternal age. The authors further identified particular maternal infections, including bacteria vaginosis as significant associated factors with preterm delivery.

In another study conducted in the United Kingdom, Nelson and Lawlor (2011) established the extent to which baseline married couple characteristics affect the probability of live birth and adverse perinatal outcomes after assisted conception is unknown. Form their study's results, it was made known among other findings that, preterm birth and low birth weight were increased if oocyte donation was required and intra-cytoplasmic sperm injection (ICSI) was not used. Again, an identified maternal factor in the name of infertility due to cervical problems was found to be associated with increased odds of all three perinatal outcomes-preterm birth, low birth weight, and macrosomia.

2.3.2 Dynamics of Preterm Birth in Developing Countries

According to a global action report by March of Dimes, PMNCH, Save the Children and WHO (2012), developing countries such as Sub-Saharan Africa and South Asia alone accounts for an estimated 60% of the world's 15 million preterm born babies every year, with its associated complications being documented as poor cognitive development, lung related problems, disabilities, growth retardation and more often Sudden Infant Death Syndrome. What really accounts for this adverse public health situations in most of these developing countries? Well, not much in-depth literature have been documented on preterm birth across multi-studies within most developing countries, but the few studies conducted have primarily attempted to identified incidence rates and causes of preterm born babies. One of such studies include a paper titled "Incidence of and socio-biologic risk factors for spontaneous preterm birth in HIV positive Nigerian women", authored by Ezechi et al., (2012). In this paper, the focus of the authors was to determine the incidence and risk factors for preterm delivery among Nigerian women diagnosed of HIV positive. The data used for their study was extracted from the database of a cohort study of the outcome of prevention of mother-to-child transmission at the Nigerian Institute of Medical Research, Lagos. Out of the 1,626 eligible women for inclusion into the study, 181 had spontaneous preterm delivery (11.1%). Spontaneous preterm delivery was found to be significantly associated with unmarried status (cOR: 1.7; 1.52-2.57), baseline CD4 count <200 cells/mm3 (cOR: 1.8; 1.16-2.99), presence of opportunistic infection at delivery (cOR: 2.2; 1.23-3.57), multiple pregnancy (cOR 10.4; 4.24 - 26.17), use of PI based triple ARV therapy (eOR 10.2; 5.52 - 18.8) in the first trimester (cOR 2.5; 1.77 - 3.52), using univariate analysis. However, after employing a multivariate analysis, and controlling for potential confounding variables including low birth weight, only multiple pregnancy (aOR: 8.6; CI: 6.73 - 12.9), presence of opportunistic infection at delivery (aOR: 1.9; CI: 1.1 - 5.7), and first trimester exposure to PI based triple therapy (aOR: 5.4; CI: 3.4 - 7.8) retained their significant association with preterm delivery. Summarizing the study's results, Ezechi et al., (2012), pin-pointed HIV positive women with multiple pregnancies, symptomatic HIV infection at delivery and first trimester fetal exposure to PI based triple therapy, as significant risk factors of spontaneous preterm delivery. Meanwhile, they recommended the use of early booking, and non-use of PI based triple therapy in the first trimester as significant antidotes for reducing the risk of preterm delivery.

In a cross-country research, Barros et al., (2011) assessed the prevalence of preterm birth among low birth weight (LBW) babies in low and middle-income countries. The authors searched and included studies on the prevalence of term and preterm LBW babies with field work carried out after 1990 in low- and middle-income countries from major databases (PubMed, LILACS, and Google Scholar). Their study used regression methods to model the occurrences. According to the 47 studies selected by the authors from 27 low- and middle-income countries, approximately half of all LBW babies are preterm, rather than one in three, as assumed in studies previous to the 1990s. From the reviewed works, Barros et al., (2011) identified low body mass index, malaria during the pregnancy cycle, smoking, pregnancy-induced hypertension, and pre-eclampsia, as common significant determinants of preterm delivery. They further revealed from 5 out of the 47 reviewed works that, preterm births are more frequent among poor populations.
Due to the estimated substantially higher number of LBW preterm babies, the authors cautioned policy-makers in low- and middle-income countries (or developing countries) to rolled-out policies in view of special health care needs for these infants.

Elsewhere in Beijing, Zhang et al, (2012) investigated into risk factors for preterm birth in five (5) maternal and child hospitals. The authors basically focused their investigation on the association between socio-demographic and obstetric factors with preterm birth in the selected hospitals. A case-control study was conducted on 1391 women with preterm delivery birth (case group) and 1391 women with term delivery (control group). Sixteen potential factors to preterm delivery were investigated and statistical analysis was performed by the use of univariate analysis and logistic regression technique. Results from the univariate analysis showed that 14 of the 16 factors considered were associated with preterm birth. Inter-pregnancy interval and inherited diseases were not risk factors. From the logistic regression results, obesity (OR=3.030, 95% CI :1.166-7.869), stressful live events (OR=5.535, 95% CI : 2.315-13.231), sexual activity (OR = 1.674, 95% CI : 1.279-2.191), placental previa (OR = 13. 577, 95% CI : 2.563-71.912), gestational diabetes melliutus (OR = 3.441, 95% CI : 1.694-6.991), hypertensive disorder complicating pregnancy (OR = 6.034, 95% CI : 3.401-10.704), history of preterm birth (OR = 20.888, 95% CI : 2.519-173.218) and reproductive abnormalities (OR = 3.049, 95% CI : 1.010-9.236) were significant risk factors associated with preterm cases. However, women who lived in towns and cities (OR = 0.603, 95 % CI: 0.430-0.846), those who had balanced diet (OR = 0.533, 95% CI: 0.421-0.675) and women who had a record of prenatal care (OR = 0.261, 95% CI: 0.134-0.570) were less likely to have preterm birth. In their concluding write-up, the authors appealed to formulate remedial factors to curtail the escalating rate of preterm birth in Beijing.

In a study by Bakhteyor et al., (2012), the researchers determined factors influencing preterm labour in women referred to hospitals in Khorramabad, from 2009 to 2010. In their work, a case-control study was conducted on 524 mothers (262 subjects in each group) referred to hospitals in Khorramabad (West of Iran) in 2009-2010, selected through consecutive sampling. Questionnaires were completed through interviews for each newborn after being examined. Data from the complied questionnaires was analysed using logistic regression. Based on the authors findings, the frequency of preterm labour in mothers under 20 was 5.83 times higher than that in mothers in the age range of 20-35 (CI : 2.99-11.37, and P<0.001). The odds ratio for preterm birth were highest for multiple pregnancies and preterm delivery in mothers with s history of obstetric complications, as delivery, low birth weight, stillbirth and abortion is seen more than that in other mothers.

Furthermore, Mokuolu et al., (2010), examined prevalence and determinants of preterm deliveries in the University of Ilorin Teaching hospital in Nigeria. Their work was based on a prospective cohort study conducted over a 9-month period at the University of Ilorin Teaching Hospital. Records of deliveries and data on maternal socio-biological and antenatal variables were collected during the study period in order to determine the prevalence and casual factors of preterm deliveries. Out of the 2489 deliveries that took place over the study period, there were 293 preterm, giving a preterm delivery rate 0f 120 per 1000 live births. Of the total deliveries, 1522 singleton deliveries which satisfied inclusion criteria were recruited; 185 of them were preterm deliveries, giving a case control ratio of 1:7 (ie., 1 in 7 are born preterm). The authors identified the significant determinants of preterm delivery in their hospital-based study as antepartun haemorrhage (P = 0.000; OR = 8.95; 95% CI: 4.06-19.78), premature rupture of the membranes (P = 0.000; OR = 6.48; CI: 4.33-9.67), previous preterm delivery (P = 0.001; OR = 3.55; 95% CI: 1.71-7.30) maternal urinary tract infection (P = 0.006; OR = 5.89; 95% CI: 1.16-27.57), pregnancy-induced hypertension (P = 0.007; OR = 3.23; 95% CI: 2.09-4.99), type of labour or delivery (P = 0.000; OR = 6.44; 95% CI: 4.42-9.38) and booking status (P = 0.000; OR = 4.67; 95% CI: 3.33-6.56). They also reported a prevalence rate of 120 per 1,000 live births. The authors affirmed that, prematurity remains a significant cause of 20% of neonatal deaths in Nigeria.

In a similar localised study in Ghana, Nkyekyer et al., (2006) primarily determined the rate of singleton preterm birth in Korle-Bu Teaching Hospital in Accra. The authors again identified the relative proportions of clinical categories of preterm births their hospital-based study. The extracted data for their study covered preterm birth cases recorded from July 1, to December 31, 2003. Out of a total of 4731 singleton births, 440 were preterm, giving a preterm rate of 9.3% for the period under review. In examining the situation, the authors revealed that, 185 (42%, [95% CI: 37.4%-46.8%]) of the preterm births followed spontaneous onset of preterm labour (group A), 82 (18.6%, [95% CI: 15.2%-22.7%]) followed premature rupture of membrane, PPROM (group B), and 173 (39.3%, [95% CI: 34.8-44.1%]) were medically indicated or iatrogenic (group C). The commonest indication for preterm delivery in group C was identified as severe pre-eclampsia/eclampsia. No differences in sex ratios, still-birth rates, and incidence of low Apgar scores were significantly found to be associated with preterm birth. In their conclusion statement, the authors iterated that, outcomes of preterm births in Korle-Bu Teaching Hospital are less favourable among indicated or iatrogenic preterm births than among spontaneous or PPROM-related preterm births. They further recommended detailed study of the causes of neonatal morbidity and mortality due to preterm birth, to be carried out in the country.

2.4 Research Gap

From the best of my knowledge, the reviewed works under this chapter have mostly concentrated on the incidence rate, causes, consequences and preventive factors of preterm birth. However, in determining the causal factors of preterm birth, the entire reviewed works focused much on maternal demographic characteristics, psychosocial factors, clinical factors, medically indicated or iatrogenic factors, obstetric or birth history of delivered mothers and prenatal/perinatal complications. Moreover, based on my checks, none of these reviewed works explicitly considered set of factors peculiar to the newborn. I also realised that, the statistical techniques extensively used for identifying significant determinants of preterm birth in the reviewed works were mostly toggled between the widely used logistic regression, and with few using Poisson regression in some specific cases. It was again revealed to us that, overwhelming majority of the works which sought to identify causal factors of preterm birth, used data concentrated on a hospital-based settings, instead of a nationwide coverage data for their respective studies. Results from hospital-based studies could be limited to small territorial areas, such as a community or district, but cannot be generalised to represent a true reflection of happenings in an entire country. However, several of the reviewed works that used the hospital-based approach reported of being handicapped due to non-existence of a centralised national data.

In addressing the identified gap in literature, this current study considered, yet, a set of the newborn's characteristics and other mentioned characteristics (maternal demographic factors, obstetric factors, etc.) from the reviewed works, to determine causal factors of preterm birth in parts of Ghana (thus, the Administrative District areas of Ahafo Ano South). The current study again employed the Bayesian binary quantile regression at three different quantiles (lower, middle/median, upper quantile) to comprehensively ascertain significant factors of preterm birth. By so doing, this current study would help fill the identified research gap on finding determinant factors of preterm birth in a middle-income setting (or from a developing country's background). It should also be put on record that the current studying, through all means possible could not have access to a centralised Ghanaian data on preterm birth, and as a result, data from a district hospital was used.

2.5 Summary

This chapter has successfully reviewed articles on prematurity or preterm birth, as deemed to be a contemporary prominent public health menace. The entire review on preterm birth cases covered specific areas such as incidence rates, causal factors, consequences and practical ways of preventing this public health menace. From the review, it was revealed that, an estimated 15 million babies are born preterm every year. Out of these recorded cases, 60% occurs annually in Sub-Saharan Africa and in South Asia. The highest rates of preterm birth are much concentrated geographically in Sub-Saharan Africa, South Asia and parts of North America respectively; with Europe recording the lowest rates of preterm deliveries or births. Complications associated with preterm birth included poor cognitive ability, kidney related problems due to immature nephrogenesis, lung disorders, delay maturation of grey matter in the cerebral cortex, patent ductus arteriosis, intra-cerebral haemorrhage, Sudden Infant Death Syndrome and more others. The review again revealed that, there are no specific causal factors of preterm birth peculiar to developed or under-developed countries. Collectively medically indicated factors, psychosocial characteristics (stress, alcohol, teenage pregnancy, etc.), multiple pregnancy, preterm premature rupture of membranes, low body mass index, malaria, pregnancy-induced hypertension, previous preterm birth history, history of obstetric complications, infections (such as bacteria vaginosis) and several other factors were identified as significant determinants of preterm birth. However, not much was identified from literature as to the scientific best practices to prevent or control the occurrences of preterm deliveries.

Chapter 3

Methodology

3.1 Introduction

The chapter mainly presents the fundamental theory of logistic and quantile regressions. It again presents the nature of the data used for the study and specifies binary logistic and quantile regression models for the data. At the initial subsection of the chapter, the study area has been given a thorough description. The chapter further shows the procedure for evaluating the regression models used for the study.

3.2 Description of Study Area

This hospital-based retrospective study on delivered mothers and their babies was confined to the Ahao Ano South District in Ghana. The district is located in the Northern-Western territory of the Ashanti Region. Altogether, the region has twenty (20) administrative municipalities and districts, with only one metropolitan area. It is well noted for its highly commercialized activities, and also serves as a haven for rural-urban drift. With all its credentials as a commercialized area, parts of the region are mostly deprived of social amenities and other infrastructural edifice that befits an urbanized region. One of such areas in the region is the Ahafo Ano South District, where this current study was conducted. The district fairly represents a section of the region, with a population of about 121,659 (Ghana Statistical Service, 2012). The main and oldest occupation of the inhabitants could predominantly be seen through the relatively high level of agriculture outputs from the district. This vast number of inhabitants can only boost of one hospital, six clinics, two health centers, a private maternity home and an orthopedic centre. The only hospital in the district serves as a ready source of primary healthcare consultation, and as a referral point for the smaller healthcare facilities in and around its catchment areas. Meanwhile, the hospital which is located in the administrative capital of the district, Mankranso, can hardly boast of one-hundred beds and other state-of-the-art facilities.

Among the most deprived communities in the district include Abasua, Mpasaso Dotiem and Bonkwaso (No. 1 & 2). These aforementioned communities are deprived of common basic survival amenities like access to portable water, adequate schools and hospital facilities. Inhabitants within these communities generally have difficulties in accessing proper primary healthcare. Whiles some confide in traditional doctors (herbalists), others seek the services of inadequate health professionals at health centres or clinics, but most are often referred to the only hospital in the district, if the need arises. The choice of Ahafo Ano South District for this study was in two folds: the first was to assess prevalence rate- and determinant factors of preterm births in some deprived parts of Ghana; and the second was based on availability of historical data on delivered mothers and their babies. Several related studies on causal effects are most often restricted to cities or developed towns or communities in Ghana, thereby creating an impression which might not fairly represent all class of people, hence, the choice to use Ahafo Ano South District. Moreover, the decision to use data from the maternity unit of the Mankranso Government Hospital to entirely represent the situation in the district was as a result of the dual purpose of the hospital which serves as primary and referral healthcare points.

3.3 Nature of Data for the Study

As explained earlier in the opening chapter of the study, the data used for the analysis was obtained from the Biostatistics Unit of the Mankranso Government Hospital. The data covers delivery cases from January 2012 to the first quarter of 2013. Relevant information on delivered mothers and their respective neonates were capture in the extracted data obtained from the database of the hospital. In all, fifteen important variables on delivered mothers and newly born babies were successfully included in the extracted data. For the purposes of this study, information on live birth cases only was included in the extracted data. Moreover, both singleton and multiple born babies were considered for the analysis. However, not all the recorded delivery cases on the hospital's database were extracted for the study. The reason for being selective could be explained in two folds: some mothers and neonates were having incomplete information across all the recorded variables, and others had complete initial information but were recorded to have either aborted or had miscarriage, hence could not bear labour to a baby.

3.4 Basic Theory of Logistic Regression

Logistic regression is a statistical technique among the family of Generalized Linear Models, popularly used to estimate the relationship between a response or outcome variable and a set of continuous and, or categorical predictor variables, Agresti (2007). By default, many analysts normally refer logistic regression to only include the binary regression but by extension, there are basically three (3) forms of logistic regression used for estimating such relationships; namely, binary logistic regression, ordinal logistic regression and multinomial logistic regression. The choice of each of these forms is based on the factor levels of the response variable. Again, all the three (3) forms of the logistic regression are based on parametric methods that usually follow the family of exponential distributions. However, each of these logistic regressions assumes different forms of these exponential distributions with emphasis on the levels of the response variables, and sometimes the shape of the random errors from the regression model. For example, a binary logistic regression model is well-known as a parametric model which generally assumes the binomial distribution (ie., a member of exponential distribution). These logistic regressions are often preferred by analysts because it allows one to examine the effect every predictor variable has on the response variable, contrast to that of black boxed models such as neural networks.

Moreover, a binary logistic regression is most often used for estimating the relationship between a response variable and predictor variable(s), when the response variable has only two factor levels. This clearly indicate that, under the binary logistic regression, the observed outcome or response variable can have only two possible factor levels or categories; for example, the response variable can assume factor levels such as "survival or casualty", "success or failure", "yes or no", "preterm or term born", etc. In such situations, the outcome or response is coded "1" and "0". The target or favoured group (usually referred to as a 'case') is mostly coded as "1" and the baseline or reference group (referred to as a 'non case'), is also coded as "0". These binary (1, 0) variables of the response are regressed on some set of predictor variables.

What happens when the response or outcome variable has more than two levels or category? The binary logistic regression will then not be applicable anymore. We shall describe the ordinal and multinomial logistic regressions as special logistic regressions known collectively as the multicategory logistic models. These multicategory models assumes that the count in the levels or categories in the response variable have a multivariate distribution, instead of the binomial distribution for the binary model (Agresti, 2007). The only difference between the multinomial logistic regression and the ordinal logistic regression is that, the count in the levels of the response variable for the latter is assumed to be ordered whereas that of the multinomial model follows a nominal scale (ie., unordered factor levels or categories). The ordinal regression is basically used to model an ordered response, and takes into account the ordered nature of the response. This obviously points out that the ordinal regression estimate the relationship between ordinal response variable (Y) and one or more continuous and, or categorical predictor variables (X_k). Contrary to the ordinal regression, the multinomial regression models the nominal response or outcome variable, by which the log odds of the outcome is modeled as a linear combination of the predictor variables. Here, the estimated relationship is solely between the nominal levels of the response and the predictor variables, contrast to that of the ordinal levels under the ordinal regression.

3.4.1 Assumptions Underlying Logistic Regression Model

There are a number of assumptions inherent in fitting a logistic regression model. Such assumptions include, but not limited to the following:

- Any predictor that is measured on a continuous scale is assumed to have a straight-line relationship with the outcome.
- The observations are independent from each other.
- In logistic regression, explanatory variables should not be highly correlated with one another because this could cause problems with estimation.
- Large sample sizes are required for logistic regression to provide sufficient numbers in both categories of the response variables. The more explanatory variables, the larger the sample size required.
- The true conditional probabilities are a logistic function of the independent variables.
- No important variables are omitted.
- No extraneous variables are included.
- The independent variables are measured without error.

- The independent variables are not linear combinations of each other.
- The dependent variable must be a dichotomy for a binary logistic regression.
- Logistic regression does not assume a linear relationship between the dependent and independent variables.
- The categories must be mutually exclusive and exhaustive, a case can only be in one group and every case must be a member of one of the groups.

3.4.2 Method of Parameter Estimation

The maximum likelihood estimation method was extensively used in the study to estimate the parameters of the specified Binary logistic regression model in subsection 3.4. Unlike the least squares estimates which normally start the process of estimation with the observed data and uses the data to compute parameter estimates; the maximum likelihood estimation procedure rather determines the likelihood or the probability of the observed data for several combinations of parameters values. The most likely set of parameter values that was found to have produced the observed data are known as the Maximum likelihood (ML) estimates. In notation the ML estimate is usually written with a chosen parameter symbol having a "hat" over it ($\hat{\pi}$ or $\hat{\beta}$). In the hindsight, we can simply explain the maximum likelihood estimate of a given parameter as the parameter value at which the likelihood or the probability of the observed data takes its greatest or maximum value. It may also be put as the parameter value at which the likelihood function takes its maximum.

In most circumstances, statistical analysts do assume a family of probability distribution for the response variable when estimating the parameters in several statistical models. In this study, we used the binomial distribution in finding the ML estimates of the logit model due to the dichotomous nature of the response variable. Let us consider the logit model;

$$Logit(\pi) = \log\left(\frac{\pi_i}{1-\pi_i} = \sum_{k=0}^{K}\beta_k x_{ik}\right) \tag{3.1}$$

where $i = 1, 2, \ldots, N$, we then started the ML estimation process by substituting the observed data into the formula for the binomial function and examined how it depends on the unknown parameter value. The joint probability density function of the response variable (Y) may be written as;

$$f(y|\beta) = \prod_{i=0}^{N} \frac{n_i!}{y_i!(n_i-y_i)!}\pi_i^{y_i}(1-\pi_i)^{x_i-y_i} \tag{3.2}$$

Here, for any n_i trails, the probability of a success is given as and the probability of successes in the response variable is taken to be $\pi_i^{y_i}$. On the contrary, the probability of $(x_i - y_i)$ failures in the response variable is also taken to be $(1-\pi_i)^{x_i-y_i}$. In equation (3.2), the joint probability density function (pdf) do expresses the values of y as a function of known, fixed values of β. The joint pdf enables us to obtain the likelihood function. The likelihood function is similar to the joint probability density function, except for the parameter of the functions. According to Agresti (2007), the likelihood function is the probability of the observed data, expressed as a function of the parameter. Over here, it expresses the values of β in terms of known, fixed values for y.

In mathematical symbols, the likelihood function may be specified in the form,

$$L(\beta|y) = \prod_{i=1}^{N} \frac{x_i!}{y_i!(x_i-y_i)!}\pi_i^{y_i}(1-\pi_i)^{x_i-y_i} \tag{3.3}$$

From the immediate equation, we can confirm that the likelihood function has the same form as the joint probability density function with the exception of the arrangement of the parameters of the two functions. We can further simplify the likelihood function in equation (3.3) into a much simpler term before finding the log likelihood function. Since the likelihood mainly deals with the product of the probability of successes ($\pi_i' s$) and failures $(1-\pi_i's)$, we closed to ignore the factorial terms (that is we treated the terms as constants) in equation (3.3).

$$L(\beta|y) = \prod_{i=1}^{N} \pi_i^{y_i}(1-\pi)^{x_i-y_i} \tag{3.4}$$

Let us perform some indices work in equation (4):

$$\begin{aligned}
\pi_i^{y_i}(1-\pi)^{x_i-y_i} &= \pi_i^{y_i}\left(\frac{(1-\pi_i)^{x_i}}{(1-\pi_i)^{y_i}}\right) \\
&= \left(\frac{\pi_i^{y_i}}{(1-\pi)^{y_i}}\right)(1-\pi)^{x_i} \\
\pi_i^{y_i}(1-\pi)^{x_i-y_i} &= \left(\frac{\pi_i^{y_i}}{(1-\pi)}\right)^{y_i}(1-\pi)^{x_i}
\end{aligned}$$

The likelihood function can now be expressed as;

$$L(\beta|y) = \prod_{i=1}^{N}\left(\frac{\pi_i^{y_i}}{(1-\pi)}\right)^{y_i}(1-\pi)^{x_i} \tag{3.5}$$

At this stage, our primary aim is to find the maximum likelihood estimates, beta hat $(\hat{\beta})$ that maximizes the likelihood function. This is done by taking the log of the likelihood function. Afterwards, the first derivative is taken to obtain the critical points. The maximum or minimum value of the function is also obtained through the second order derivative of the same function.

Let us now take the e of both sides in equation (3.1). The resultant equation is written as;

$$\left(\frac{\pi}{1-\pi}\right) = e^{\sum_{k=o}^{K}\beta_k x_{ik}} \tag{3.6}$$

After solving for π in equation (3.6), we get;

$$\pi = \frac{e^{\sum_{k=o}^{K}\beta_k x_{ik}}}{1+e^{\sum_{k=o}^{K}\beta_k x_{ik}}} \tag{3.7}$$

By putting equations (3.6) and (3.7) into (3.5), we now have the likelihood function as;

$$L(\beta|y) = \prod_{i=1}^{N} \left(e^{\sum_{k=o}^{K} \beta_k x_{ik}}\right)^{y_i} \left(1 - \frac{e^{\sum_{k=o}^{K} \beta_k x_{ik}}}{1 + e^{\sum_{k=o}^{K} \beta_k x_{ik}}}\right) \tag{3.8}$$

We can again simplify equation (3.8) to have a much manageable terms;

$$\left(e^{\sum_{k=o}^{K} \beta_k x_{ik}}\right)^{y_i} = e^{y_i \sum_{k=o}^{K} \beta_k x_{ik}}$$

$$\left(1 - \frac{e^{\sum_{k=o}^{K} \beta_k x_{ik}}}{1 + e^{\sum_{k=o}^{K} \beta_k x_{ik}}}\right) = \left(\frac{1 + e^{\sum_{k=o}^{K} \beta_k x_{ik}}}{1 + e^{\sum_{k=o}^{K} \beta_k x_{ik}}} - \frac{e^{\sum_{k=o}^{K} \beta_k x_{ik}}}{1 + e^{\sum_{k=o}^{K} \beta_k x_{ik}}}\right)$$

$$\therefore \qquad \left(1 - \frac{e^{\sum_{k=o}^{K} \beta_k x_{ik}}}{1 + e^{\sum_{k=o}^{K} \beta_k x_{ik}}}\right) = \left(1 + e^{\sum_{k=o}^{K} \beta_k x_{ik}}\right)^{-n_i}$$

The simplified version of the likelihood function can now be written as;

$$L(\beta|y) = \prod_{i=1}^{N} \left(e^{y_i \sum_{k=o}^{K} \beta_k x_{ik}}\right) \left(1 + e^{\sum_{k=o}^{K} \beta_k x_{ik}}\right)^{-n_i} \tag{3.9}$$

Let us take the natural log of the likelihood function to get the log likelihood equation;

$$\ell(\beta) = \prod_{i=0}^{N} \left[\left(y_i \sum_{k=0}^{K} \beta_k x_{ik} \right) - x_i \cdot \log\left(1 + e^{\sum_{k=o}^{K} \beta_k x_{ik}}\right) \right]$$

In sum y_i from $i = 1, 2, \ldots N$, we obtain the log likelihood equation as;

$$\ell(\beta) = \left[\sum_{i=0}^{N} y_i \left(\sum_{k=0}^{K} \beta_k x_{ik} \right) \right] = \sum_{i=0}^{N} y_i \frac{\partial}{\partial \beta_k} \left(\sum_{k=0}^{K} \beta_k x_{ik} \right) \tag{3.10}$$

At this stage, we shall find the first partial derivatives with respect to each β and thereafter equate each of them to zero in order to obtain the maximum likelihood estimates (the critical values).

$$\frac{\partial}{\partial \beta_k}\left[\sum_{i=0}^{N} y_i\left(\sum_{k=0}^{K}\beta_k x_{ik}\right)\right] = \sum_{i=0}^{N} y_i \frac{\partial}{\partial \beta_k}\left(\sum_{k=0}^{K}\beta_k x_{ik}\right)$$
$$= \sum_{i=0}^{N} y_i x_{ik}$$

$$\frac{\partial}{\partial \beta_k}\left[-n_i \cdot \log\left(1+e^{\sum_{k=o}^{K}\beta_k x_{ik}}\right)\right] = -n_i \cdot \frac{1}{1+e^{\sum_{k=o}^{K}\beta_k x_{ik}}} \cdot \frac{\partial}{\partial \beta_k}\left(1+e^{\sum_{k=o}^{K}\beta_k x_{ik}}\right)$$
$$= -n_i \cdot \frac{1}{1+e^{\sum_{k=o}^{K}\beta_k x_{ik}}} \cdot e^{\sum_{k=o}^{K}\beta_k x_{ik}} \cdot \frac{\partial}{\partial \beta_k}\left(\sum_{k=o}^{K}\beta_k x_{ik}\right)$$
$$= -n_i \cdot \frac{1}{1+e^{\sum_{k=o}^{K}\beta_k x_{ik}}} \cdot e^{\sum_{k=o}^{K}\beta_k x_{ik}} \cdot x_{ik}$$
$$= -n_i \cdot \frac{e^{\sum_{k=o}^{K}\beta_k x_{ik}}}{1+e^{\sum_{k=o}^{K}\beta_k x_{ik}}} \cdot x_{ik}$$

But;

$$\pi_i = \frac{e^{\sum_{k=o}^{K}\beta_k x_{ik}}}{1+e^{\sum_{k=o}^{K}\beta_k x_{ik}}}$$

This implies that;

$$\frac{\partial}{\partial \beta_k}\left[-n_i \cdot \log\left(1+e^{\sum_{k=o}^{K}\beta_k x_{ik}}\right)\right] = -n_i \pi_i x_{ik}$$

Therefore, the first partial derivative of the log likelihood for each β is given as;

$$\frac{\partial \ell(\beta)}{\partial \beta_k} = \sum_{i=0}^{N} y_i x_{ik} - n_i \pi_i x_{ik} \tag{3.11}$$

We finally put each of the $k+1$ equations to zero and solve for each β_k to obtain the maximum likelihood estimates for β (critical values). The second - order derivative is further obtain to verify the β values (critical values) at which the log likelihood is maximized.

3.4.3 Odds and Odds Ratio

The odds ratio is basically described by Agresti (2007) as another measure of association between paired variables. It occurs as a parameter in the most important type of model for categorical data. The odds of an event occurring is simply defined as the ratio of the probability that such event will occur, to the probability that the event will never occur. It is often used as a descriptive summary statistics, and plays a key role in logistic regression. Unlike other measures of association for paired binary data such as the relative risk, the odds ratio specifically treats the two variables being compared symmetrically, and its estimations are obtained using some types of non-random samples. Moreover, the odds ratios are widely used in several areas of statistical applications (eg., medical reports, ecological study, ect.) for meaningfully estimating the relationship between two binary variables. Such ratios enable analysts to generally examine the effects of other variables on that estimated relationship using logistic regression. It also allows analysts to conveniently interpret estimated parameters from logistic regressions.

In application to this current study, the odds ratio was employed for easy and understandable interpretation of the tendency to deliver a preterm or term baby. For example, if the probability of a mother delivering preterm is denoted as pi, and the probability of delivering a term baby is $(1-\pi)$, then the odds of delivering a preterm baby by the mother is defined to be;

$$Odds = \frac{\pi}{1-\pi} \tag{3.12}$$

Over here, the odds are said to be nonnegative (ie., measured on the positive scale), with value greater than one (1) when a preterm delivered baby is more likely than a term baby. The odds ratio can easily be obtained from the specified odds. Suppose the event of delivering preterm or term baby follows a data in a 2 by 2 (2×2) table, and within row one (1), the odds of preterm delivery are represented as; $Odds_1 = \frac{\pi_1}{1-\pi_1}$, and that of row two (2) are denoted as; $Odds_2 = \frac{\pi_2}{1-\pi_2}$. The computed ratio of the odds from the two rows is what many referred to as odds ratio:

$$Odds\ ratio\ (\theta) = \frac{odds_1}{odds_2} = \frac{\pi_1/(1-\pi_1)}{\pi_2/(1-\pi_2)} \tag{3.13}$$

This simply means there clear distinction between odds ratio and a measure of relative risk. The odds ratio is a ratio of two specified odds, whereas a relative risk measures the ratio of two probabilities (thus, the ratio that specifies the probability of the occurrence of an event to the probability of the non-occurrence of such event).

In general, the odds ratio $R_{S,D}$ that respectively compares the odds of event E occurring in group S and D is expressed as the ratio between the two odds. This is denoted by;

$$Odds\ ratio\ (R_{S,D}) = \frac{odds(E_S)}{odds(E_D)} = \frac{P(E_S)/(1-P(E_S))}{P(E_D)/(1-P(E_D))} \tag{3.14}$$

The odds ratio could also be seen as a statistical measure of effect size, which mainly describes the strength of association or non-association between two binary data values. Apparently, if the estimated odds ratio is one (1), then the odds are the same for the event occurring in the two groups. Estimated odds ratio values further away from 1 in a given direction mostly represent stronger association.

In practice, let us consider the degree of association between delivery outcome (preterm or term), and antenatal attendance or otherwise, by delivered mothers using the concept of odds ratio.

From Table 3.1, an estimate for the probability of a mother delivering preterm in this case, provided she attended antenatal is denoted as; $P(E_{attended}) = \frac{23}{57} = 0.4035$. This leads us to obtain the odds of a mother delivering a preterm baby, provided she attended antenatal as; $Odds(E_{attended}) = \frac{0.4035}{1-0.4035} = 0.6764$. Again, the probability of a mother delivering on term, provided she never attended antenatal is estimated as; $P(E_{never-attended}) = \frac{35}{167} =$

Table 3.1: Delivery Outcome and Antenatal Care

	Outcome	
	preterm	term
attended antenatal	23	34
never-attended antenatal	35	132

0.2096. Hence, the odds of having a term baby is given by; $Odds(E_{attended}) = \frac{0.2096}{1-0.2096} = 0.2652$. Now, the odds ratio comparing the odds of a mother delivering preterm, provided she attended antenatal with the odds of delivering a term baby, provided a woman attended antenatal is expressed as; $Odds\ ratio(R_{attended,\ never-attended}) = \frac{0.6764}{0.2652} = 2.5505$.

This estimated odds ratio could be interpreted to mean that, the odds of a mother delivering a preterm baby is 2.55 times more likely for women who attended antenatal than for women who never attended antenatal. From this example, mothers are more likely to deliver preterm babies if they attend antenatal.

3.4.4 Specifying a Binary Logistic Regression Model for this Study

In an attempt to model the dichotomous outcome of preterm and term births by delivered mothers at Mankranso Government Hospital, the binary logistic regression model was adopted in this study as one of the main statistical techniques. The binary logistic regression model is used to specifically explain the relationship between a dichotomous response variable and one or more categorical and, or continuous independent or explanatory variable(s). It is a special regression model classified among the family of Generalized Linear Models (GLM). It is only applicable in situations where the dependent or the response variable being considered in the regression model can be expressed in a binary form. For instance, in a research to generally explain whether the use of contraceptives among Ghanaian women depends on occupation, age, marital status, education, religion, ect., one of the most appropriate statistical techniques that might be used by an analyst would be that of the binary logistic regression model. In this current scenario, the response variable would be categorized as a binary data (that is, '1' for contraceptive users and '0' for non-contraceptive users). This statistical technique is most widely used in modeling cases of which the response variable is strictly dichotomous or binary.

To apply the binary logistic regression technique in modeling the data on preterm and term deliveries, obtained from the Biostatistics Unit at the Mankranso Government Hospital, the regression model was specified as;

$$\log\left(\frac{P(Y=1|X)}{1-P(Y=1|X)}\right) = \log\left(\frac{\pi}{1-\pi}\right) = \alpha + \sum_{k=o}^{K} \beta_k x_k \tag{3.15}$$

where, alpha (α) denotes the constant term of the regression model, beta (β_k) are the coefficients to be estimated and X_k are the set of predictor variables incorporated into the model. Here, the response variable (Y) was coded as "1" for babies born preterm and '0' for babies who were delivered on term. This clearly means that the response or outcome variable in the study was categorized into a dichotomous response data, where '1' represents babies born preterm and '0' for babies born on term. The conditional probability in equation (15), $P(Y=1|X)$ describes the likelihood or the tendency of pregnant mothers to deliver preterm babies, given some predictor variables ($X = x_1, x_2, \ldots, x_p$). The tendency of recording a term born baby was also expressed as $1-P(Y=1|X)$ in the same equation (15). The ratio of measuring the effect size of delivering a preterm baby to that of a term baby, given some predictor conditions, expressed in equation (15) as; $\left(\frac{P(Y=1|X)}{1-P(Y=1|X)}\right)$ is popularly known as the odds ratio. A logit transformation of this odds ratio was explicitly defined in equation (15) to obtain a binary logit regression model for the data under consideration. In the specified regression equation, there are fourteen (14) predictor variables which combine to predict the response variable (preterm or term birth). All such fourteen (14) predictor variables were categorical variables.

In predicting the dichotomous outcome of a mother delivering either a preterm or term baby, the fourteen (14) categorical predictors considered in the specified logit model in equation (15) were the maternal age of delivered mothers ('3'=below 20, '2'=20-30, '1'=31-40, '0'=41 & above); estimated blood lost ('1'=below 500, '0'=500 & above); APGAR score ('2'=1-3, '1'=4-6, '0'=7 & above); fetal heart rate ('2'=below 120, '1'=120-160, '0'=above 160) and antenatal care ('1'=attended at least once, '0'=never attended). Other predictors include place of abode ('1'=rural, '0'=town); baby's sex ('1'=male, '0'=female); number of conceived fetuses ('1'=multiple, '0'=single); IPT ('1'=no dose, '0'=at least one dose); and delivering type ('2'= SVD, '1'cesarean, '0'=vacuum extraction). The remaining variables were birth weight ('1'=LBW, '0'=NBW); pregnancy complication ('1'=complication recorded, '0'=no complication); gravity ('2'=0-2, '1'=3-5, '0'=above 5) and parity ('2'=0-2, '1'=3-5, '0'=above 5). Altogether, these set of categorical predictors were incorporated into the binary logit model to predict the outcome or the response variable (preterm or term born baby). The parameters to be estimated in the specified binary logit model in equation (12) are the alpha (α) and beta (β) terms in the regression model. Suppose all the fourteen (14) categorical predictors in the model are set to zero, then the predicted log-odds in favor of $Y = 1$ (delivering preterm baby) would eventually be reduced to a constant term (α). This means each term of the categorical predictions would rather contribute to the estimated log-odds in favour of the success (delivering preterm baby). For instance, for each increase or decrease in a predictor (X_k) in equation (15), there is predicted to be an associated increase or decrease of beta (β_k) units in the log-odds in favour of delivering a preterm baby. For more clarity of explanation, because the response variable is modeled using a log transformation, the interpretation of the estimated coefficients in the specified model would be generally based on the exponential transformation of the estimated coefficients, which has been earlier defined as the odds ratio.

Table 3.2: Extracted Maternal & Newborn's Variables

	Dummy Variables (Coding)
Maternal Variables	
Age	"0"=41 & above; "1"=31-40; "2"=20-30; "3"=below 20
Abode	"0"=Town; "1"=Rural
Foetuses	"0"=Single; "1"=Multiple
IPT	"0"=At least one dose; "1"=No dose
ANC	"0"=Never attended; "1"=At least one attendance
Preg. Comp.	"0"=No complication; "1"=Complication recorded
Gestation	"0"=37 & above; "1"=Below 37 weeks
EBL	"0"=500 & above; "1"=Below 500
Delivery	"0"=Vacuum; "1"=Ceasarean; "2"=Spontaneus
Parity	"0"=Above 5; "1"=3-5; "2"=0-2
Gravidity	"0"=Above 5; "1"=3-5; "2"=0-2
Newborn's Variables	
Newborn weight	"0"=Normal weight; "1"=Low weight
Sex	"0"=Female; "1"=Male
FHR	"0"=Above 160; "1"=120-160; "2"=Below 120
Apgar Score	"0"=7 & above; "1"=4-6; "2"=1-3

3.4.5 Evaluation of the Specified Binary Logistic Regression Model

After fitting any statistical model to a specified data, it is bestowed on the analyst to assess how well such model fits the data. This is to say, not all fitted models perform quite well. The act of assessing the performance of how best a model fits a data is popularly known as Goodness-of-fit. Under this statistical principle, the most appropriate or optimal model is always chosen to fit the data under consideration. This Goodness-of-fit principle also applies to a fit from a logistic regression model. Analysts are generally encouraged to check how best a regression model fits a data before making inferences. It is widely believed that, the hallmark of every good statistician is the person's ability to make accurate and precise inferences. Inferences based on a non-performing logistic regression model or a regression model that does not fit a data quite well, may mislead analysts into making wrong inferences about events or the occurrences of events. In line with this, the study made use of the Hosmer and Lemeshow Goodness-of-fit test and the likelihood ratio test in assessing the adequacies of the fit from the specified binary logit model.

Hosmer and Lemeshow (2000) re-iterated an earlier Goodness-of-fit approach, which was introduced in the 1980s by the two scholars. Under the Hosmer and Lemeshow approach, sizeable groups of cases are formed in a way in which the total numbers of observations per category are approximately equal, and a Goodness-of-fit statistic is computed by comparing the observed and predicted number of events in each group formed. Each group is supposed to have an observed count of subject with each outcome or response, and a fitted value for each outcome. The fitted value for an outcome is the sum of the estimated probabilities for that outcome for all observations in that particular group. The Hosmer and Lemeshow statistic, denoted by X^2_{HL}, is obtained by computing;

$$X^2 = \sum \left[\frac{(0-E)^2}{E} \right] \tag{3.16}$$

where, O is the observed frequency and E is the expected frequency. The rationale is that, the closer the expected frequencies are to that of the observed, then the smaller in value the statistic would be. This practically means, smaller values of this statistic indicates a good fit to the data, whereas relatively larger values of the statistic indicates a model which is not a good fit to the data under consideration. Moreover, the statistic does not have exactly a limiting chi-squared distribution. However, Hosmer and Lemeshow (2000) pointed out clearly that, when the number of distinct patterns of covariate values for the observed data is close to the sample size, the distribution is generally approximated by a chi-squared distribution with degrees of freedom (df) equal to the number of groups minus two (2), thus, $\chi^2(g-2)$.

Another way to assess the adequacy of a fitted model is to compare it with a more general model with the maximum number of parameters that can be estimated. Here, the likelihood ratio test is basically used to compare the likelihood of a full-fitted model with all predictor variables included, with the likelihood of the initial model fit (null model). The likelihood ratio test statistic is denoted by;

$$G^2 = 2\log\frac{L}{L_0} = 2(\log L - \log L_0) \tag{3.17}$$

where, L_0 is the likelihood of the initial model (null model) and L is the likelihood of the full-fitted model. The test statistic G^2 has approximately a chi-squared distribution χ^2 with k degrees of freedom. The degree of freedom (k) is determined by the number of predictors in the model. Practically, if the test statistic is found significant, it indicates that, for all combined, the predictor variables contribute significantly to the prediction of the response or outcome variable.

3.4.6 Basic Concept of Quantile Regression

Quantile regression was introduced and made popular around the 1970s by two renowned econometricians, namely Koenker and Bassett. With their most celebrated paper titled, "Regression quantiles", Koenker and Bassett (1978) generally introduced, yet, another statistical technique among the family of regression techniques, which has since being widely embraced by many scholars. Their technique is basically an extension on the linear regression model. It allows analysts to estimate several rates of change in all parts of the distribution of an observed response or outcome variable in a regression analysis. In simple terms, the quantile regression statistically models the relation between a set of categorical and, or continuous variables and specific quantiles or percentiles of the response variable under consideration. Such regression models flexibly allows analysts to specify changes within the distribution (ie., changes in quantiles) of the observed response variable.

Unlike the normal linear regression which models the relation between one or more specified covariates (X_k) and the conditional-mean function of the response variable ($Y|X_k$), the quantile regression simply models the relation between one or more specified covariates (X_k) and the conditional-quantile function of the response variable ($Q(\tau)|X_k$). According to Brian and Barry (2003), for most data which have more than a single slope (rate of change) describing the relationship between a response variable and its associated predictor variables, the quantile regression is used to estimate such multiple rates of change (slope) from the minimum to the maximum response, thereby providing a more comprehensive picture of the relationship between variables missed by other regression methods such as the simple/multiple linear regression and the logistic regression. This simply means, the quantile regression model holistically study the potential effects on the shape of the distribution of the response variable, given some predictors.

3.4.7 Specifying and Estimating Binary Quantile Regression Model

As earlier described, in the normal linear regression models, the rate of change in the mean of the distribution of the response variable is estimated as a function of a set of predictor variables. Such models simply estimate the conditional mean in the response distribution (Y), given some set of covariates (X_k), which is denoted by $E(Y|X_k)$. This conditional-mean model is interpreted as the average in the population of the response (Y) values, which correspond to a fixed value of the covariates (X_k). These regression models are described by Koenker and Hallock (2001) as most often demonstrating incomplete picture of the relationship between a response variable and set of covariates, especially in the presence of heterogeneous variances. This therefore means, it is possible to fit regression curves to several parts of the distribution of a response variable, but not to only the average (mean) part of the distribution of the response variable. These special properties of quantile regressions override even the Generalized Linear Models, of which logistic regression forms a family. Although, the family of Generalized Linear Models estimate changes in the variances of the response variable (Y) with changes in the mean based on the family of exponential distributions, but the main focus of such models is to obtain better estimates of the rates of change in the mean of the response variable (Y). Like the normal linear regression, the Generalized Linear Models do not provide a complete picture of the relationship between all parts of the distribution of the response variable (Y) and the predictor variables, which must surely occur in the presence of heterogeneous variances.

In application to this current study, the quantile regression model was specified as:

$$Q_y(\tau|X_k) = \beta_0(\tau)X_0 + \beta_1(\tau)X_1 + \beta_2(\tau)X_2 + \ldots + \beta_k(\tau)X_k + \epsilon \tag{3.18}$$

Where $Q_y(\tau|X_k)$ denotes the conditional-quantile function at different given percentiles or quantiles (τ), $\beta_k(\tau)$ represents the coefficients to be estimated at the different quantiles (τ) and X_k are the set of covariates or predictor variables. For this study, the response variable (delivering a preterm or term baby) was modeled at three (3) different quantiles (lower = 5^{th}; median = 50^{th} quantile; upper = 90^{th} quantile), given fourteen (14) predictor variables (X_k). These predictor variables have already being specified in the earlier subsection. The effects of the estimated coefficients on the response in the specified quantile regression model vary due to the τ^{th} quantile of the unknown error distribution. This suggests that the quantile regression model assumes a semiparametric method for its estimation. The deterministic part $(\beta_0(\tau)X_0 + \beta_1(\tau)X_1 + \ldots + \beta_k(\tau)X_k)$ can be estimated using parametric methods, while the random error part of the model (ϵ) follows no parametric probability distribution form, unlike that of the binary logistic regression whose error might follow the binomial distribution.

The parametric part of the binary quantile regression may either be estimated using the Frequentist (classic) approach or the Bayesian approach. Under the Frequentist approach, the estimates are obtained by formulating an optimization function which minimizes the sum of weighted absolute deviations, where these weights are basically asymmetric function of τ. Proponent of the Frequentist approach was pioneered in the works of Manski (1975; 1985); where the Maximum Score Estimator was first used to estimate the parameters of binary quantile regressions. Ever since the introduction of the Maximum Score Estimator algorithm, several scholars in various studies have in one way or the other criticized the ability of the algorithm to achieve global optimal estimates. For example, Kim and Polland (1990) punched loopholes into Manki's algorithm by proving that, it has a slow convergence rate and a much complicated asymptotic distribution. A recent study by Dries and Dirk (2010) further criticized the Maximum Score Estimator, as imposing extremely weak assumptions on the distribution of the error term. It was made clear from their work that, the Frequentist approach for estimating binary quantile regression suffers major technical drawbacks. These include difficulties in optimizing the regression parameters, building confidence intervals and making statistical inference from such estimated parameters. To address the optimization difficulty of the binary quantile regression parameters, Horowitz (1992), introduced yet another algorithm which sought to smooth the Maximum Score function proposed by Manki, to achieve continuity and differentiability. Horowitz explained that his approach would lead to an asymptotically normal distribution, which might rectify the problem of optimizing the estimates. However, in a work by Florios and Skouras (2008) to review all empirical applications of the two Frequentist approaches to binary quantile regression, they explicitly concluded that, none of the specified algorithms or approaches guarantees a global optimal estimate. The practical nature of complexity for the estimated parameters to achieve convergence under the Frequentist approach limits the usefulness of the estimated parameters for any meaningful inferences. Due to the problematic nature of estimating the binary quantile regression parameters under the Frequentist approach; this study adopted the Bayesian approach in addition to the Frequentist approach, for estimating parameters of the binary quantile regression.

Dries and Dirk (2010) generally recommended the Bayesian approach as most appropriate for estimating binary quantile regression parameters. According to them, the joint posterior density of the unobservable beta parameter β and the response variable y^* given the data $y = (y_1, y_2, y_3, \ldots, y_n)$, and the chosen quantile of interest, τ, could be written as:

$$\pi(\beta, y^*|y, \tau) \;\alpha\; \pi(\beta) \prod_{i=1}^{n} \{I(y_i^* > 0)I(y_i = 1)\} + I(y_i^* \leq 0)I(y_i = 0)Fy^*(y_i*; x_i\beta, 1, \tau) \tag{3.19}$$

where, $\pi(\beta)$ represents the prior on the binary quantile regression coefficients and $I(\bullet)$ denotes indicator function (in this case, binary indicators). It is much obvious from the joint posterior density in (16) that the posterior distribution does not conform to common known kinds of distributions. However, with the aid of Markov Chain Monte Carlo (MCMC) algorithms, the posterior distribution can straightforwardly be computed. Dries and Dirk (2010) argued that, splitting up the complicated posterior in the posterior distribution of β conditional on y^* and in the posterior distribution of y^* conditional on β facilitates sampling from the joint posterior. By so doing, they were of the view that, one of the two fully conditional distributions will result to a known distributional form. In application of the Bayesian estimation approach to this current study, the posterior density of β given y^8, τ, and the dataset was specified as:

$$\pi(\beta, y^*|y, \tau) \; \alpha \; \pi(\beta) \prod_{i=1}^{n} Fy^*(y_i^*; x_i\beta, 1, \tau) \tag{3.20}$$

where, y^* is the response variable of delivering on term or preterm, y represents the dataset, x_i is a vector of explanatory variables, and τ has been specified to include lower quantile (5^{th} quantile), median quantile (50^{th} quantile) and an upper quantile (90^{th} quantile). This specified conditional posterior density was taken as the posterior density for the regression parameters to be estimated in the binary quantile regression. For more on current practical applications to Bayesian estimates for binary quantile regression coefficients, readers are directed to the works of Chambers et al., (2012) and Migueis et al., (2013).

3.5 Summary

This chapter of the study has thoroughly presented and explained the research methodology employed for the entire work. In all, two statistical techniques were introduced and further given detailed explanation, as to the basic reason behind adopting each of these techniques. The binary logistic regression was used to model the log odds in favour of a mother delivering a preterm baby, given a chance in any of the predictor variables. In an attempt not to miss the effect of any predictor variable(s) on the entire distribution of the response variable (ie., the outcome of delivery), the binary quantile regression technique was also adopted. Under the binary quantile regression, the effects of the predictors were specified at different quantiles or percentiles of the response variable. This was expected to help estimate the effects of the set of covariates specified in the quantile regression model at different rates of change (ie., changes in quantiles) of the response variable. The chapter, at its initial stage, gave a brief description of the area where the study was successfully undertaken.

The next chapter, which is titled ”Presentation and Analysis of Results”, presents to entire empirical results obtained and gives an elaborate analysis such results.

Chapter 4

Data Analysis and Results

4.1 Introduction

This Chapter basically presents detailed results and analysis from the study. In general, the presentation and analysis of the study's results are being put into three main captions: descriptive analysis, bivariate analysis, and multivariate analysis (from the specified logistic regression model and that of the binary quantile regression). Under each of these captions, there has been an elaborate discussions of the various results obtained.

4.2 Descriptive Analysis

In this subsection, a vivid descriptive analysis of preterm or term delivery occurrences has been clearly outlined. The counts and associated percentages of recording preterm or term delivery cases, as distributed across several maternal variables and selected characteristics of the newborns have been presented in Table 4.1. This subsection therefore gives exclusive and comprehensive analysis based on the results shown in the table.

From Table 4.1, 336 newborns, representing 47.3% of the entire live birth cases were born preterm (thus, below 37 weeks of gestation). This indicates that, approximately, every 4 out of 9 live born babies in the Ahafo Ano South District are born preterm. This is quite alarming due to the adverse health effects normally associated with preterm babies. Preterm birth cases were highly recorded (63.9%) among teenage mothers (below age 20). Middle age mothers (31 - 40) and those aged above 40 years recorded among themselves the lowest cases of preterm deliveries (41.2% and 20.0% respectively). The evidence of

Table 4.1: Descriptive Statistics of Delivery Outcome Across Key Variables

Predictor Variables		Outcome Variable: Gestation Preterm Birth N (%)	Term Birth N (%)	Total
Maternal Age	Below 20	94 (63.9%)	53 (36.1%)	147
	20 - 30	169 (45.2%)	205 (54.8%)	374
	31 - 40	68 (41.2%)	97 (58.8%)	165
	41 & Above	5 (20.0%)	20 (80.0%)	25
Baby's sex	Male	169 (45.4%)	203 (54.6%)	372
	Female	167 (49.4%)	171 (50.6%)	338
Baby's weight	Below 2.5g	91 (60.7%)	59 (39.3%)	150
	2.5g & Above	245 (43.7%)	316 (56.3%)	561
Abode	Rural	268 (48.7%)	282 (51.3%)	550
	Town	68 (42.2%)	93 (57.8%)	161
IPT	No Dose	83 (57.2%)	62 (42.8%)	145
	1 Dose	67 (47.2%)	75 (52.8%)	142
	2 Dose	91 (43.3%)	119 (56.7%)	210
	3 Dose	95 (44.4%)	119 (55.6%)	214
Antenatal	Attended	320 (47.2%)	358 (52.8%)	678
	Never attended	16 (50.0%)	16 (50.0%)	32
Complication	Yes	28 (54.9%)	23 (45.1%)	51
	No	308 (46.7%)	352 (53.3%)	660

teenage pregnancy in the district could be seen as a challenge, reading from the number of teenage mothers' reported in Table 4.1. It could be witness from the table that, 147 birth cases, representing 20.7% of the 711 live birth cases were delivered to teenage mothers. This again suggests that, approximately, every 2 out of 9 pregnant mothers in the district are teenage mothers. With respect to the newborn's sex or gender status, it was realized that female born babies recorded slightly higher proportion (49.4%) of preterm cases among their cohorts, as compared to that of the preterm birth cases among their male born counterpart. Babies born with low birth weight (LBW¡2.5g), recorded a substantial proportion (60.7%) of preterm born cases. From the table, 150 newborns,

Table 4.1: Descriptive Statistics of Delivery Outcome Across Key Variables (Contd.)

Predictor Variables		Outcome Variable: Gestation Preterm Birth N (%)	 Term Birth N (%)	Total
Delivery type	SVD	261 (48.9%)	273 (51.1%)	534
	CS	44 (38.6%)	70 (61.4%)	114
	V	27 (49.1%)	28 (50.9%)	55
	SVD/V	3 (50.0%)	3 (50.0%)	6
	1 - 3	4 (44.4%)	5 (55.6%)	9
Apgar-1min	4 - 6	56 (50.5%)	55 (49.5%)	111
	7 & Above	276 (46.7%)	315 (53.3%)	591
	1 - 3	2 (66.7%)	1 (33.3%)	3
Apgar-5min	4 - 6	12 (50.0%)	12 (50.0%)	24
	7 & Above	322 (47.1%)	362 (52.9%)	684
	Below 120	7 (41.2%)	10 (58.8%)	17
FHR	120 - 160	316 (47.7%)	347 (52.3%)	663
	Above 160	13 (43.3%)	17 (56.7%)	30
Fetuses	Multiple	35 (38.9%)	55 (61.1%)	90
	Singleton	301 (48.5%)	320 (51.5%)	621
EBL	Below 500	311 (48.4%)	331 (41.6%)	642
	500 & Above	25 (36.2%)	44 (63.8%)	69
	0 - 3	242 (51.6%)	227 (30.8%)	469
Parity	4 - 6	84 (41.4%)	119 (30.8%)	203
	7 & Above	10 (25.6%)	29 (30.8%)	39
	0 - 3	173 (52.9%)	154 (47.1%)	327
Gravidity	4 - 6	119 (42.8%)	159 (57.2%)	278
	7 & Above	44 (41.5%)	62 (58.5%)	106
		336 (47.3)	375 (52.7)	711

representing 21.1% of the overall live birth cases were born with weight below 2.5g (LBW).

To another situation, results from Table 4.1 shows moderately higher percentage (48.7%) of preterm cases among mothers residing in rural settings of the Ahafo Ano South District. Moreover, pregnant mothers exposed to intermittent preventive treatment (IPT) with 1, 2, and 3 doses given at different periods within the pregnancy cycle, recorded somehow declining proportions of preterm birth cases (47.2%, 43.3% and 44.4% respectively) among their cohorts. However, mothers who never took the IPT dose are seen from the table to have been associated with high percentage (57.2%) cases of preterm babies. Overwhelmingly, majority (678: 95%) of the delivered mothers attended antenatal, at least once in their pregnancy cycle. The few who never attended antenatal had 50% cases of preterm deliveries. This indicates a positive attitude towards antenatal attendance by pregnant mothers in the Ahafo ano South District. Among delivered mothers who had at least one complication during pregnancy, it could be inferred from the table that 54.9% cases of preterm deliveries were aligned to them. This means complications during pregnancy cycles may result to preterm delivery. It could further be inferred from the results shown in the table that moderate proportions were fairly recorded across the delivery types considered. The APGAR, an abbreviation which means appearance, pulse, grimace, activity and respirations, is the assessment of the newborn's rating colour, heart rate, stimulus response, muscle tone, and respirations on a scale of zero to two, for a maximum possible score of 10. The score assists delivery attendance or practitioners to decide whether or not a newborn is in need of resuscitation. It is taken on the newborn at the first and/or fifth minutes of successful delivery. From the results shown in the table, newborns that scored below 7 (out of the maximum 10 marks) recorded higher proportions of preterm delivery cases. This depicts that, the lower or averages the APGAR score, the higher the percentage of recording preterm delivery cases. In furtherance, the fetal heart rate of fetuses taken whiles inside their mothers' womb was also considered. From the results shown in Table 4.1, majority of the newborns had normal fetal heart rate (120 - 160). It could further be observed that the occurrences of preterm births were fairly - proportionally distributed among the categories outlined under the fetal hear rate factor.

In addition to the earlier discussed maternal variables, we again looked critically at the number of fetuses conceived to a pregnant mother. In all, 90 babies, representing 12.7% of the overall recorded live births were as a product of multiple fetuses. Among the products from the multiple and single fetuses, 38.9% and 48.5% of cases involving preterm births were respectively associated to these cohorts. The percentage cases of preterm births among the estimated blood lost (EBL) cohorts were considerably lower. However, results from Table 4.1 show that, the percentage cases of preterm births are relatively higher among mothers with lower parity (51.6%) and gravidity (52.9%) respectively. We could therefore infer that, the higher the parity and gravidity levels, the lower the proportions of recording preterm birth cases.

4.3 Bivariate Analysis

To comprehensively demonstrate and unveil individual determinant factors associated with the response or dependent variable of delivering preterm or term babies, a bivariate statistical technique was employed. The likelihood-ratio chi-square test of association was the bivariate technique used for determining such significant association between each predictor variable and the response or outcome variable. Agresti (2007) expressed the likelihood-ratio statistic for testing association in any $(I \times J)$ contingency table as;

$$G^2 = 2 \sum n_{ij} \log \left(\frac{n_{ij}}{\hat{\mu_{ij}}} \right) \tag{4.1}$$

where n_{ij} represents the observed cell count (or frequencies) and $\hat{\mu_{ij}}$ denotes the estimated expected frequencies. According to Agresti (2007), the test statistic has approximately a chi-square distribution with $(I-1)(J-1)$ degrees of freedom. The evidence of association is said to be obviously identified if the test statistic produces a value which can be observed at the farthest end of the chi-square distribution (or $p < 0.05$).

Based on a 5% significant level, the results of the likelihood-ratio chi-square test of association shown in Table 4.2 indicate that, maternal age, baby's weight, number of fetuses conceived to pregnant women, intermittent preventive treatment (IPT), gravidity and parity were individual determinant factors significantly associated with delivering preterm or term babies. From the results shown in the table, factors such as maternal age, baby's weight and parity had strong association (at 1% significance) with the response variable than any other predictor variable considered. However, several of the predictor factors

Table 4.2: Likelihood Ratio Chi-Squared Test of Association

	Outcome Variable: Gestation		
Predictor Variables	Value	df	Sig[a]
Maternal Age	27.680	3	0.000
Baby's sex	1.124	1	0.289
Baby's weight	13.749	1	0.000
Place of Abode	2.114	1	0.146
Intermittent Preventive Treatment	7.804	3	0.040
Antenatal Care	0.096	1	0.757
Pregnancy Complications	1.286	1	0.257
Delivery Type	4.124	3	0.240
Apgar - 1min	0.556	2	0.757
Apgar - 5min	0.540	2	0.763
Fetal Heart Rate	0.482	2	0.786
Number of Fetuses	8.923	1	0.047
Estimated Blood Lost	3.783	1	0.052
Parity	14.067	2	0.001
Gravidity	7.811	2	0.020

Sig[a] - 0.05 significance level; df - degree of freedom

considered indicated no statistical significance with the response. From the table, factors such as APGAR score under one and five minutes, fetal heart rate (FHR) and antenatal attendance showed much stronger non-significance with the tendency to deliver preterm or term babies. Altogether, the non-significant predictor variables in Table 4.2 could be classified statistically as non-determinant factors of preterm or term born babies under the bivarite analysis.

Moreover, the predictor factors identified in Table 4.2 needs to be further studied. We may need to know which level(s) within these categorical predictors are more or less susceptible to preterm deliveries. There again, after identifying the causal factors, we still have to study the extent of effects of such factors on the response variable. All these cannot be achieved using this bivarite technique. To clearly demonstrate the causal effects and understand the extent to which the levels of these categorical predictors have on the response variable, the next subsection introduces readers to results and analysis of two multivariate statistical techniques: binary logistic regression and binary quantile regression. These techniques would only not show significant association, but further gives deeper insight to cause-and-effect, goodness-of-fit issues, and other easily interpretable estimates such as estimated coefficients, estimated intervals (posterior probability interval or confidence interval), odds ratio, etc.

4.4 Analysis from the Specified Logistic Regression Model

As already explained, one of the multivariate statistical techniques used for analyzing the cause-and-effect of delivering preterm or term born babies was the binary logistic regression. The dichotomous outcome or response of delivering preterm or a term baby was regressed against some carefully selected covariates of the mother and newborn's characteristics. The results from the binary logit fit are shown in Table 4.3. From the table, the maximum likelihood estimates of the model's coefficients, standard error, significance of the covariates, point estimates of the odds ratio and 95% confidence interval for the odds ratio are reported successfully. At the initial stage of the binary logit fit, fourteen (14) covariates were considered. However, by the use of the backward conditional variable selection approach, only six (6) of such covariates were entered into the final fit. The choice to use the backward conditional variable selection approach at the expense of the forward variable selection and that of the purposeful selection, proposed by Hosmer and

Lemeshow (2000) was as a result of its flexibility to the researcher. This is not to say the other variable selection approaches are not good to use, but rather, is all about the prerogative of the analyst. Although, there are six (6) variables reported in Table 4.3, but four (4) of such variables showed statistical significance, whiles the remaining two (2) variables are non-significant (using the 0.05 level of significance). However, the entire six (6) variables were entered into the final logit using the backward selection method. This suggest that the two (2) non-significant variables that entered the final fit only serves as confounders to the other four (4) significant covariates. Though, not statistically significant, but these confounders contributes to the entire adequacy fit of the final binary logit fit.

From the results shown in Table 4.3, low birth weight babies (LBW ¡ 2.5g) had 120.9% tendency of recording preterm deliveries, compared to babies with normal birth weight (NBW). In other words, the odds of having a preterm delivered baby is more than 100% likely among babies born with low birth weight, than babies with normal birth weight. This variable (baby's weight) is seen as a strong determinant factor (even at 1% significant level) of predicting the likelihood of a mother delivering a term or preterm baby. Moreover, the number of fetuses conceived to a pregnant mother showed up as another significant determinant factor of predicting the dichotomous response of having born preterm or at term. It could again be seen from the table that mothers who conceived single fetuses had 0.594 (40.6%) times less likelihood to have recorded preterm birth than colleague mothers who conceived multiple fetuses in just one pregnancy cycle. This means, pregnant mothers found to conceive multiple fetuses needs special medical attentions since they are highly prone to delivering preterm born babies. Furthermore, the age of the delivered mother was also found to have shown strong statistical significance with the binary response variable. Here, teenage mothers (delivered mothers below age 20) were 7.177 times more likely to record preterm deliveries than their counterpart mothers' age above 40. Also, pregnant mothers age from 20 to 30 and those in the age bracket of 31 to 40 years were respectively 2.265 and 2.009 times more likely to deliver preterm babies. From the foregoing, we could clearly infer that, teenage pregnant mothers are more susceptible to deliver babies before term (preterm birth). In a further situation, the intermittent preventive treatment (IPT) administered to pregnant mothers turned out to be, yet, another strong significant predictive factor of the tendency to deliver preterm or at term. From the table, pregnant mothers who were not exposed or abstained themselves from the intermittent preventive treatment were 1.878 times more likely to deliver their babies before term (preterm delivery) as compares to those who took three (3) doses of the intermittent preventive treatment drugs at separate periods. The situation was much different as those who took one (1) and two (2) doses of the IPT drug recorded decreasingly 1.534 and 1.507 times more tendencies of preterm delivery cases than those mothers who took all the three (3) required doses of the IPT drug. This therefore suggest that, pregnant mothers who are not on the IPT drug have high tendencies of delivering before term, and such tendencies decreases as pregnant mothers take one (1) to two (2) doses of the IPT drug. Conversely, pregnant mothers who take all three (3) required doses of the IPT drug have less tendency or likelihood to experience preterm delivery.

It is a convention for any well-meaning statistical analyst to first examine the adequacies of his or her fit before embarking on any serious analysis. Well, in this current study, we hold-high such convention. As a result of this, some adequacy checks were carried out before adjudging the final binary logit fit as good for further analysis. Theses adequacy checks are reported in the subsequent subsection (subsection 4.3.1).

4.5 Goodness-of-fit for the Logit Regression

To assess the adequacy of the logit fit, the Hosmer and Lemeshow Goodness-of-fit test and the likelihood-ratio test were employed for such evaluation. These adequacy checks were

Table 4.3: Maximum Likelihood Estimates from the Specified Logit Regression

Predictor Variables		Estimate	S.E	Sig	Odds ratio Exp(B)	95% CI	
	Intercept	-1.007	0.345	0.003	****	****	****
Baby's sex	Male	-0.274	0.159	0.084	0.760	0.557	1.037
	Ref: Female						
Baby's weight	Below 2.5g	0.793	0.206	0.000	2.209	1.477	3.306
	Ref: 2.5 & above						
No. of fetuses	Single	-0.521	0.253	0.039	0.594	0.362	0.975
	Ref: Multiple						
Maternal age	Below 20	1.971	0.542	0.000	7.177	2.479	20.78
	20 - 30	0.817	0.242	0.001	2.265	1.409	3.641
	31 - 40	0.698	0.209	0.001	2.009	1.334	3.025
	Ref: 41 & above						
IPT	No Dose	0.630	0.228	0.006	1.878	1.201	2.936
	1 Dose	0.428	0.227	0.059	1.534	0.984	2.393
	2 Dose	0.410	0.250	0.101	1.507	0.923	2.461
	Ref: 3 Dose						
EBL	Below 500	0.497	0.277	0.073	1.644	0.955	2.828
	Ref: 500 & above						

Hosmer and Lemeshow Test

Chi-square	df	Sig
5.88	8	0.661

Likelihood-ratio test - pvalue=0.00 < 0.05;
Negalkerke R-square - 21.05

necessitated to make accurate and precise inferences about the occurrences of the events under study. Generally, inadequate fits may normally mislead analysts to either make wrong inferences or unreliable declarations of determinant factors or causes of special events. Such academic blunders may directly mislead stakeholders or people in authority into implementing wrong measures to solve nothing closer to the situation at hand. To avoid these unwarranted mess, analysts have been always advice to embark on some sought of adequacy checks after a model's fit. Based on this, the logit fit of the current study was checked for adequacies.

From Table 4.3, the likelihood-ratio test results indicate that the final logit fit significantly (based on 5% significance) gives precise predictions as compared to the baseline or null model's fit. This means, the final logit fit with covariates, significantly performs than the null logit fit, with respect to predictive accuracies. Moreover, in assessing the final logit fit, the Hosmer and Lemeshow test results shown in the table, with $\chi^2(8)$ of 5.88 and p ¿ 0.05, give clear indication of how quite well the data fit the logit model. These two diagnostic tests unanimously confirm adequate fit of the data to the final logit model.

4.6 Results and Analysis from the Binary Quantile Regression

Under this section, the estimated parameters from the binary quantile regressions are overly presented and thoroughly discussed. Initially, the study adopted the Frequentist and the Bayesian methods of estimation, to possibly obtain global optimal estimates for the earlier specified quantile regression parameters. However, from the study's preliminary results, the Frequentist approach had much difficulty with estimation convergence, under each of the specified binary quantile regressions at different selected quantile levels ($\tau = 0.05, 0.50, 0.90$). Spurious and unreliable estimates which barely have any meaningful statistical inference were mostly produced by the use of the Frequentist approach of estimation. This result supports the findings of Kim and Polland (1990); who through their work, vehemently criticized one of the core Frequentist approaches, for repeatedly showing slow convergence rate in estimating parameters of binary quantile regressions. Owing to this unfortunate empirical finding, only the results from the Bayesian estimation approach for the binary quantile regressions have been reported. As mentioned in the previous chapter, the binary quantile regressions for this study were specified at three different quantiles or percentiles: These included, a lower quantile regression ($\tau = 0.05$); median quantile regression ($\tau = 0.50$); and an upper quantile regression ($\tau = 0.90$). The results obtained from the Bayesian approach for the three specified binary quantile regressions are generally reported in the next subsections.

4.6.1 Analysis from the 5^{th} Bayesian Binary Quantile Regression

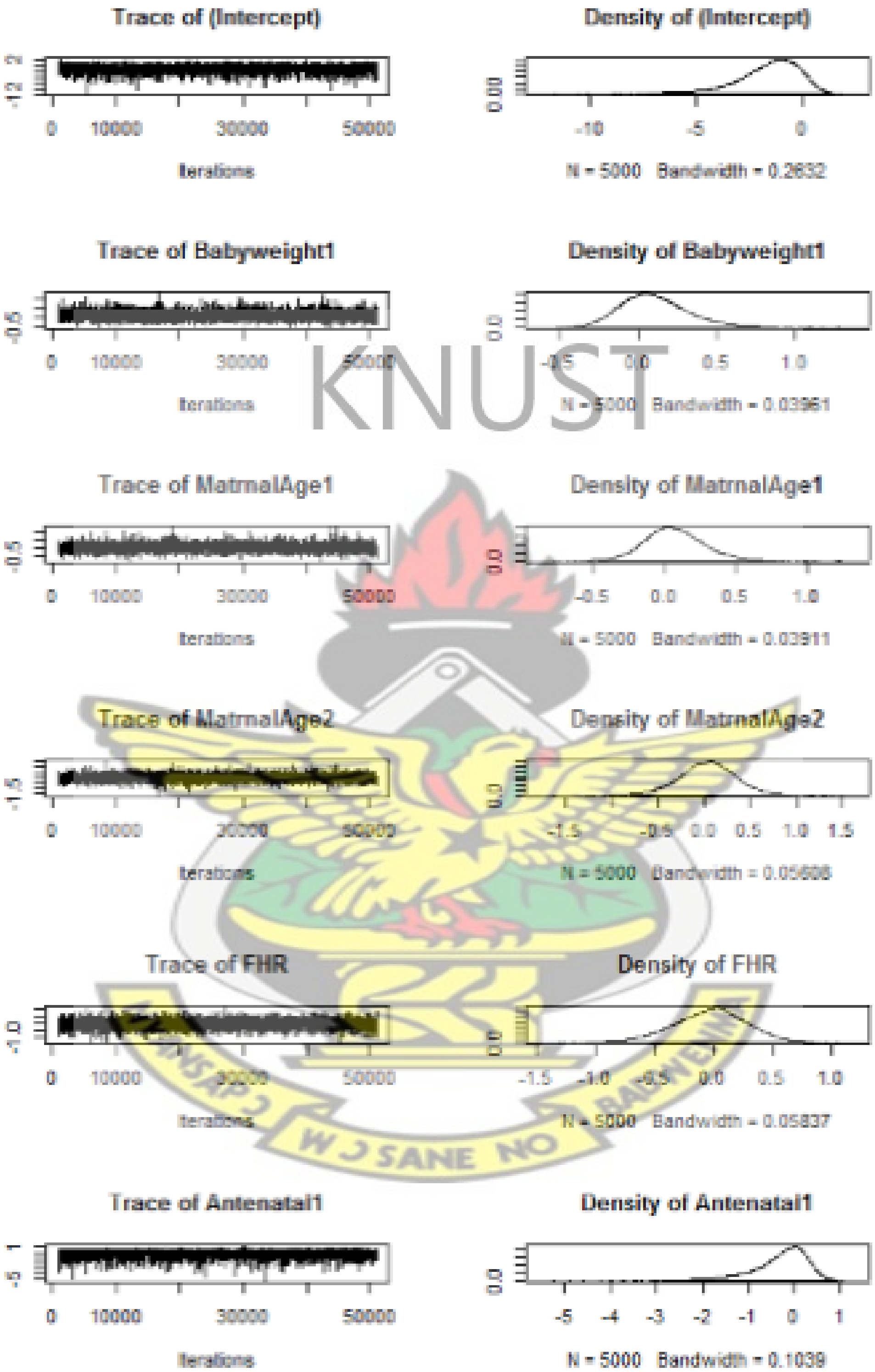
For this current subsection and the remaining two subsections of the chapter, the Bayesian results to the binary quantile regressions are thoroughly discussed. The entire Bayesian results presented over here includes, the posterior point estimates (mean), the posterior standard deviation, 95% Posterior Probability Intervals (or Credible Intervals), trace and density plot for each posterior point estimates, and plots for the posterior distributions. Results from Table 4.4 present the Bayesian quantile estimates for the 5^{th} (0.05) binary quantile regression. From the reported estimates, we were much interested in assessing the association between each predictor on the response variable, as well as the corresponding effect magnitude from such associations. From the posterior point estimates (mean) shown in the table, low weight of the newborn (below 2.5g) , teenage mothers (below 20yrs) and middle-age mothers (20-30yrs), APGAR scores under one (1) minute and five (5) minutes, and number of fetuses conceived by a mother, had positive impact on preterm birth. Other predictor variables such as intermitted preventive treatment (IPT) with no dose taken, complication during the pregnancy cycle and low parity (0-3) also showed positive impact on preterm delivery cases. Moreover, predictor variables such as fairly aged mothers (31-40), estimated blood lost (EBL), fetal heart rate (FHR), antena-

Table 4.4: Maximum Likelihood Estimates from the Specified Logit Regression

Dependent Variable: Gestation (preterm or term birth)					
Quantile (τ) = 0.05				95% Bayesian Credible Interval	
		Mean	St. Dev	Lower	Upper
Constant		-1.580250	1.50183	-5.2773	0.5795
Babyweight	[Below 2.5]	0.107008	0.21853	-0.2621	0.5955
MaternalAge	[Below 20]	0.065539	0.22138	-0.3459	0.5955
	[20-30]	0.034871	0.30689	-0.5849	0.6301
	[31-40]	-0.186524	0.94041	-2.5646	1.1969
EBL	[Below 500]	-0.086407	0.41104	-1.0992	0.5885
APGAR1	[Below 5]	0.089420	0.26355	-0.3509	0.6991
APGAR5	[Below 5]	0.332938	0.70911	-1.0697	2.1093
FHR	[Below 120]	-0.031951	0.30863	-0.6670	0.5395
Antenatal	[Attended]	-0.329059	0.66007	-2.0227	1.0054
Abode	[Rural]	-0.007753	0.18886	-0.4345	0.3254
Babysex	[Male]	-0.017148	0.15224	-0.3128	0.2906
Foetus	[multiple]	0.051079	0.28856	-0.4353	0.7220
IPT	[No Dose]	0.018694	0.06679	-0.1072	0.1566
DeliveryType	[CS]	-0.036556	0.27507	-0.6505	0.4344
	[CS]	-0.186561	0.40337	-1.2234	0.3920
	[V]	-2.696032	3.31339	-11.5147	1.0098
Complication	[Yes]	0.259122	0.44813	-1.0037	1.3797
Gravidity	[0-3]	-0.028733	0.21346	-0.4857	0.3949
	[4-6]	-0.140366	0.36402	-0.9543	0.4954
Parity	[0-3]	0.022547	0.23971	-0.4606	0.4993
	[4-6]	-0.053118	0.63894	-1.5045	1.0251

tal attendance, mothers residing in towns, male born babies, delivery type, gravidity and moderately high parity (4-6) recorded negative impacts on the likelihood for a woman to deliver preterm. However, from the 95% Credible Intervals (Posterior Probability Intervals) shown in the table, we could infer that maternal age, APGAR score within five (5) minutes, antenatal, delivery type, complication during the pregnancy cycle and parity, showed significant varying effects on the tendency to deliver preterm (preterm birth). This is so because, the posterior distribution of the estimated coefficient β_j for predictor variables are not scattered around zero, or the posterior distribution for β_j associated with each of the identified predictor variables is far away from zero. This indicates that, the null hypothesis of no significant effect ($\beta_j = 0$) is rejected; meaning, the identified set of predictor variables are statistically important contributors to preterm birth.

From the posterior estimates in Table 4.4, it could be deduced that, the risk of preterm birth decreases by 0.186524 cases in the lower quantile for mothers aged between 31-40, as compared to their colleague mothers aged from 41 yrs and above. In a sharp contrast, teenage (below 20yrs) and middle-age mothers respectively recorded increases of 0.065539 and 0.034871 cases of preterm births, as compared to the aged mothers (41 yrs and above). This indicates that, the latter cohorts are more susceptible to preterm delivery. In addition, the risk of delivering preterm babies increases at the lower quantile by 0.089420 whenever the APGAR score of babies are below the average mark of five (5). Comparably, mothers who attended antenatal for at least once recorded significant decrease of 0.329059 preterm delivery cases, than colleague mothers who never attended antenatal care services; meaning, there is a low risk of recording preterm delivery cases among pregnant mothers who patronizes antenatal services. Furthermore, it could be inferred from Table 4.4 that, all the categorized deliver types had negative significant varying effects on preterm delivery at the lower quantile. However, the risk of preterm birth increases by 0.022547 cases among low-parity (0-3) mothers than cases among mothers with high parity (7 and above). In swift contradiction to the latter finding, middle-parity (4-6) mothers recorded negative significant effects on preterm delivery; meaning, low-parity mothers are more exposed to preterm delivery.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Iterations
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Iterations
Density of MatrnalAge2
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Iterations
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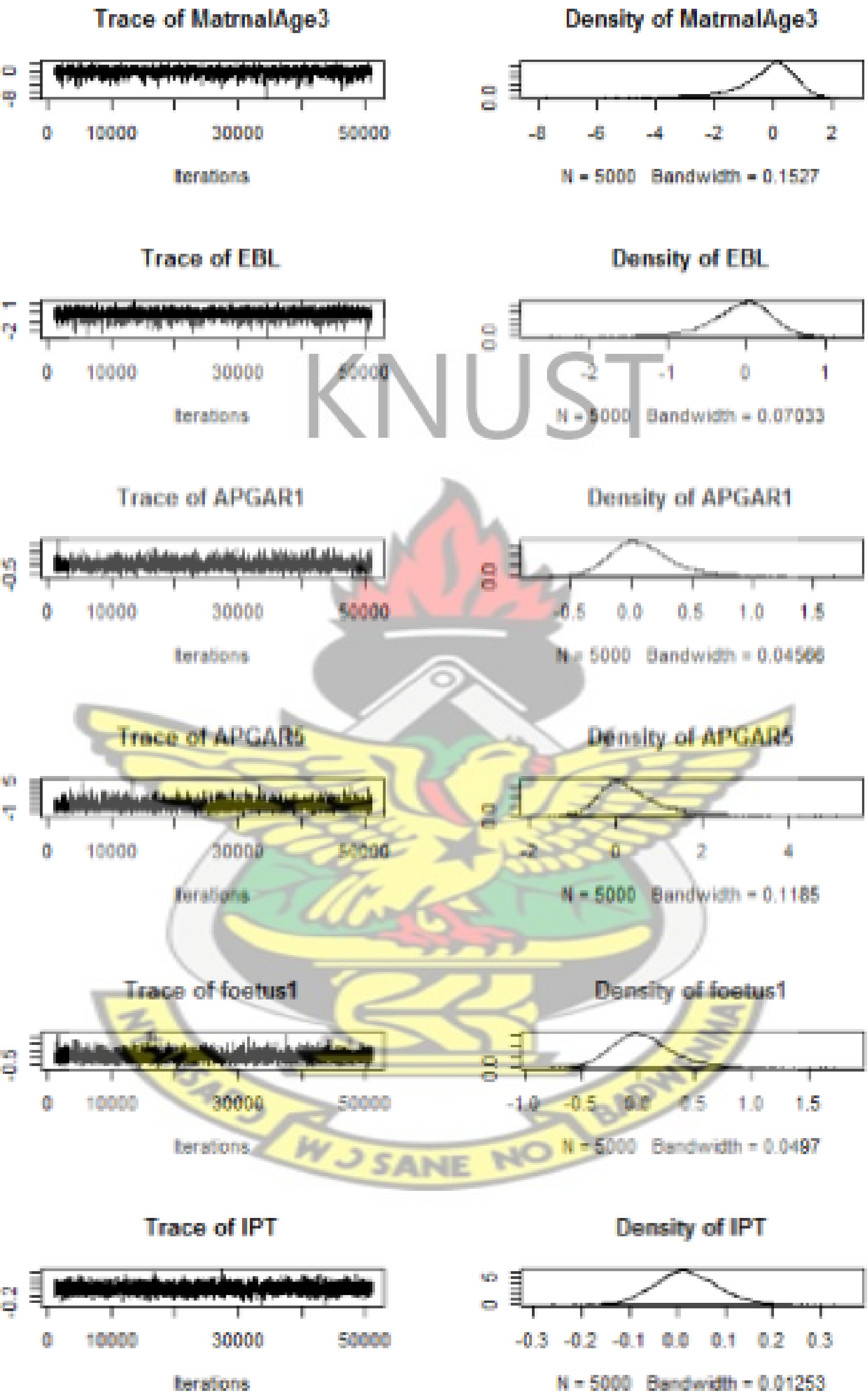
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Density of APGAR1
Iterations
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Trace of APGAR5
Density of APGAR5
Iterations
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Iterations
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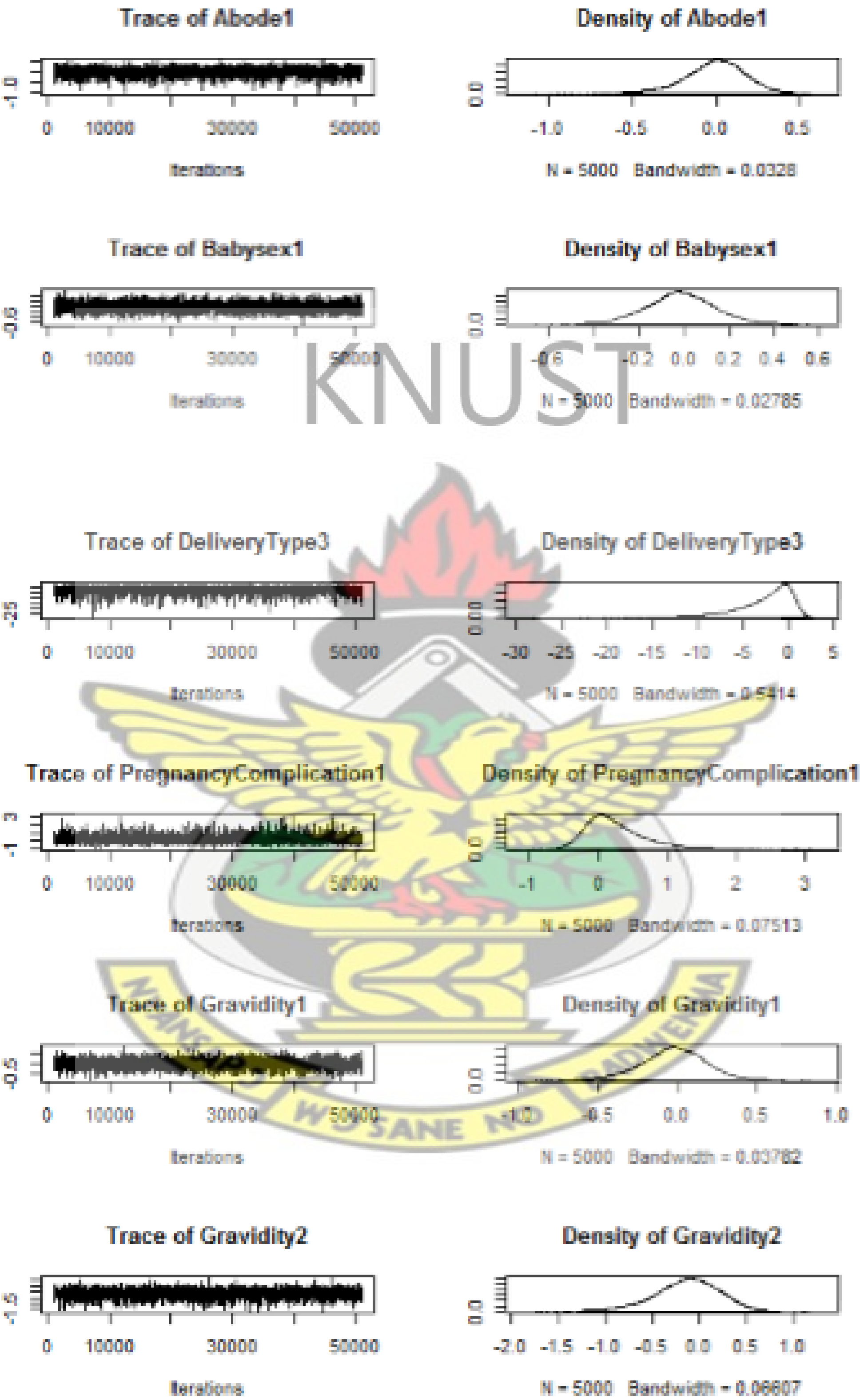
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Density of DeliveryType3
Iterations
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Trace of PregnancyComplication1
Density of PregnancyComplication1
Iterations
N = 5000 Bandwidth = 0.07513
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Iterations
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Trace of Gravidity2
Density of Gravidity2
Iterations
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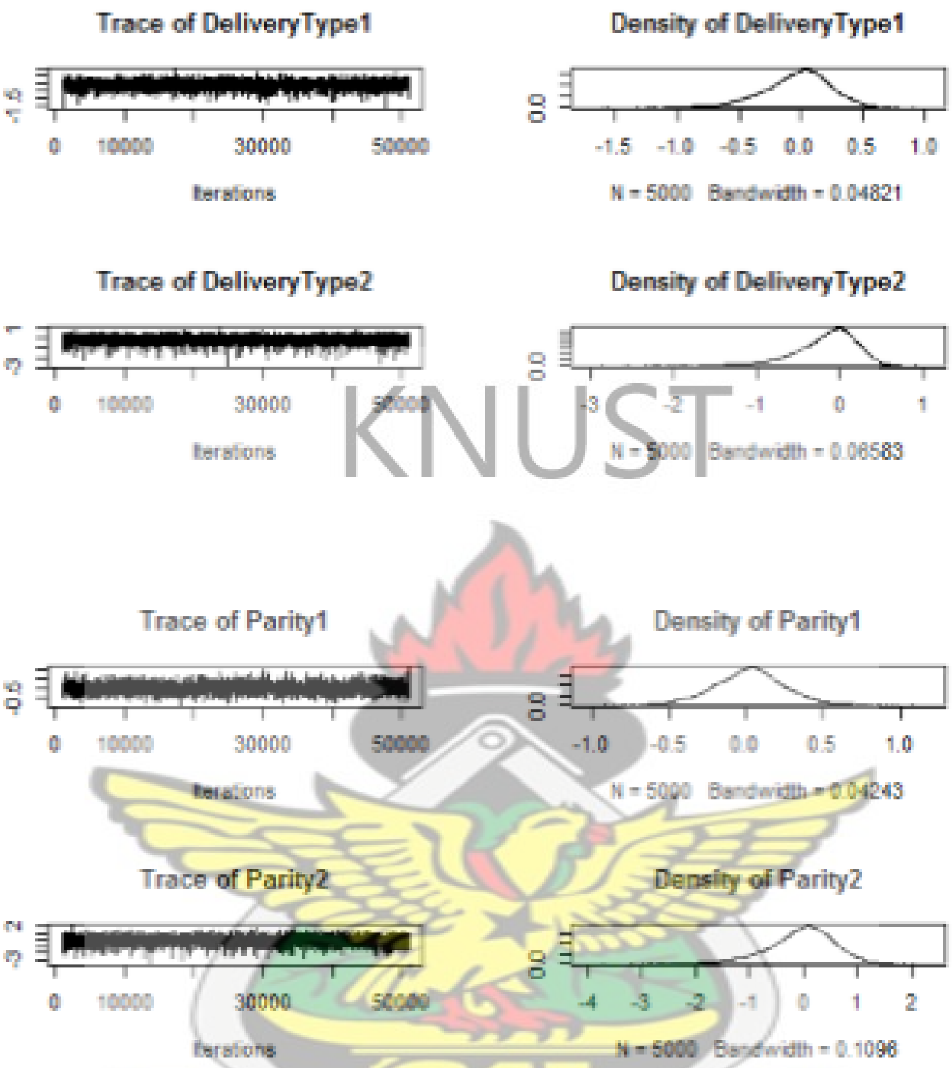


Figure 4.1: Trace and density plot of each estimated Bayesian point estimate at $\tau = 0.05$

A trace and density plots for each estimated posterior point estimate (mean) and its associated Credible Interval is shown in Figure 4.1. The trace plot serves as a diagnostic check for each posterior point estimate. Since the initial samples are obtained from the prior distribution, there is a need for the samples to generally converge to the true posterior distribution; hence, the diagnostic check for convergence has become necessary. Most often, few parallel chains are run from divergent starting points. Afterwards, the number of iterations is specified, and the sample values are plotted for each chain. The plot of the sample values for each is what we popularly referred to as trace plot. Moreover, the time taken for the chains to "mix" together is always taken as the time for convergence. Manually, convergence is reached when the samples (or trace) pattern behave randomly, but scattered around a stable mean value. From Figure 4.1, it could clearly be concluded by easily visualizing the trace plot for each posterior estimate that, total convergence has been reached. On the other hand, the posterior density plot is another diagnostic tool used to ascertain the parallel lines assumption of checking to verify whether the slope difference of the posterior estimate is lower than the zero value. Critical observation at the plots in the right panel of Figure 4.1, well suggest that all the posterior density plots for the predictor variables, except maternal age, APGAR score within the first five (5) minutes, antenatal, delivery types and complication during the pregnancy cycle, overlaps on the zero value. This further suggests that, these set of predictor variables have varying significant statistical influence on determining preterm birth or the tendency to deliver preterm.

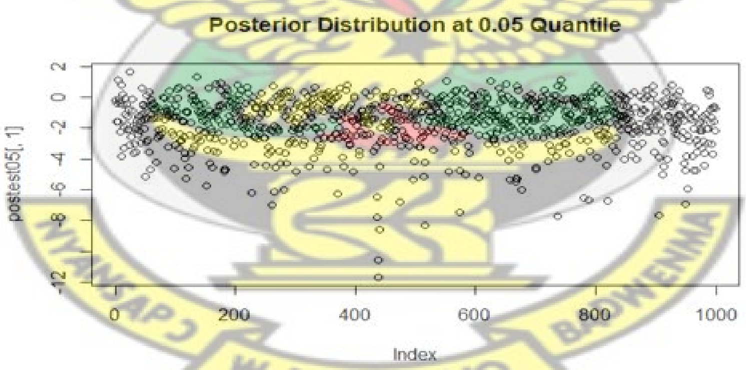


Figure 4.2: Posterior Distribution at the Lower Quantile ($\tau = 0.05$)

The posterior distribution at the 5^{th} (0.05) quantile or percentile of the response variable is shown in Figure 4.2. This plot helps to visualize the way and manner the posterior mass probability is distributed at the lower quantile. From the figure, it could be inferred that, the posterior probability mass is randomly distributed with some few scattered points.

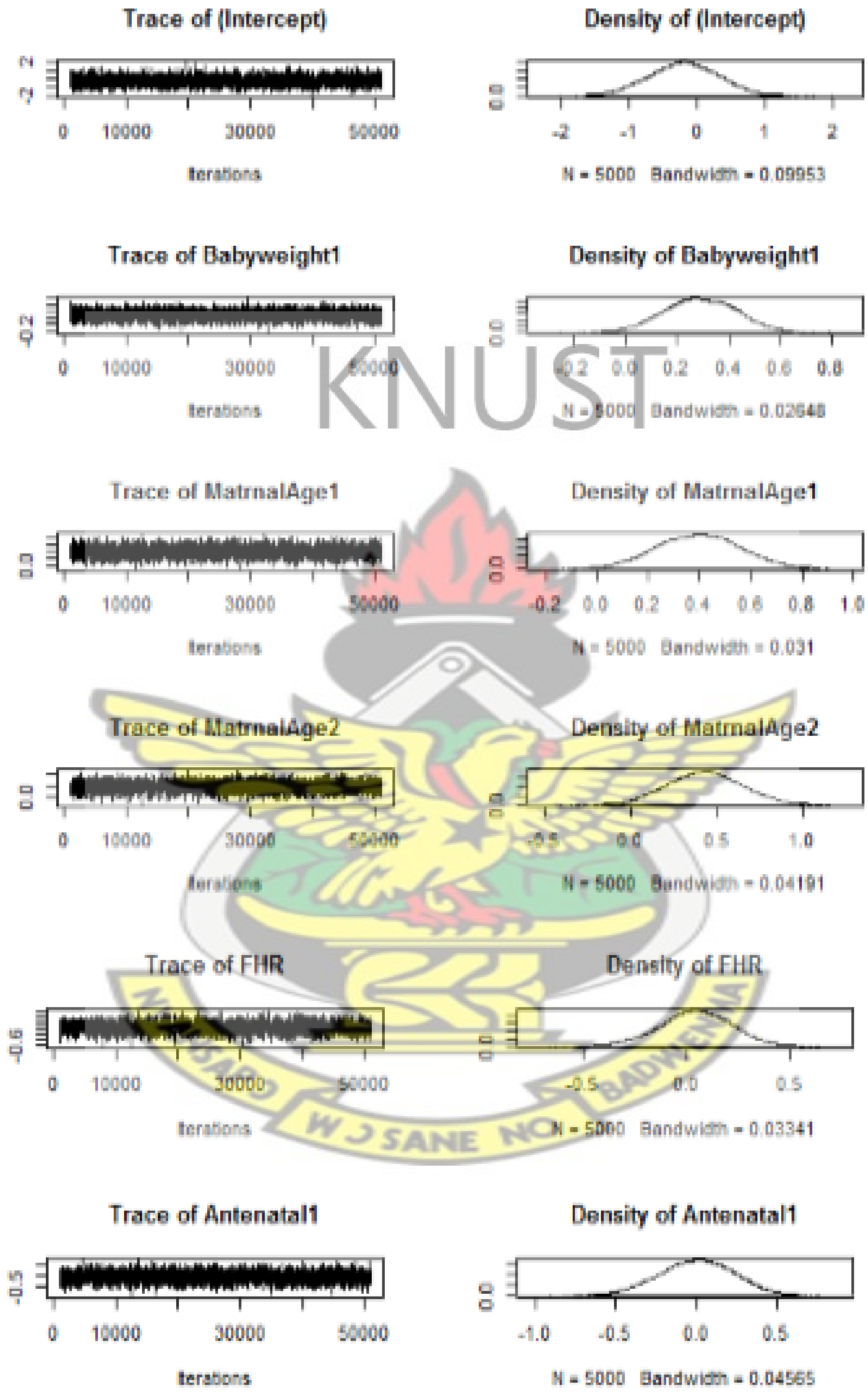
4.6.2 Analysis from the 50^{th} Bayesian Binary Quantile Regression

The 50^{th} Bayesian quantile regression is popularly referred by many as Bayesian median quantile regression. Under this regression, the level of association and effect size of the posterior variables on the middle or median (50^{th} percentile) of the distribution for the response variable are examined.

From Table 4.5, baby's weight, maternal age, estimated blood lost (EBL), fetal heart rate (FHR), antenatal, place of abode, intermittent preventive treatment (IPT), delivery type and parity, were recorded to have had positive effects on preterm birth. However, their respective effect sizes are not statistically significant in predicting preterm birth, or the likelihood to deliver preterm babies. This could be attest from the 95% Credible Intervals which generally overlap over the zero value. Although, the identified predictor variables over here were found to have shown positive effects on preterm birth, they were equally not significant, and could not offer any meaningful statistical inference.

Table 4.5: Maximum Likelihood Estimates from the Specified Logit Regression

Dependent Variable: Gestation (preterm or term birth)					
Quantile (τ) = 0.50				95% Bayesian Credible Interval	
		Mean	St. Dev	Lower	Upper
Constant		-0.197526	0.51574	-1.20055	0.7937
Babyweight	[Below 2.5]	0.289590	0.13720	0.01974	0.5537
MaternalAge	[Below 20]	0.396524	0.16062	0.08739	0.7145
	[20-30]	0.429697	0.21731	0.01301	0.8562
	[31-40]	0.612869	0.32365	-0.02765	1.2521
EBL	[Below 500]	0.115678	0.17656	-0.24126	0.4550
APGAR1	[Below 5]	-0.003788	0.13493	-0.26871	0.2615
APGAR5	[Below 5]	0.070559	0.24704	-0.40341	0.5534
FHR	[Below 120]	0.043040	0.17860	-0.31859	0.3845
Antenatal	[Attended]	0.002519	0.23656	-0.46858	0.4514
Abode	[Rural]	0.083150	0.12116	-0.16179	0.3211
Babysex	[Male]	-0.089458	0.10281	-0.29170	0.1088
Foetus	[multiple]	-0.174794	0.14583	-0.45488	0.1148
IPT	[No Dose]	0.057804	0.04783	-0.03459	0.1519
DeliveryType	[CS]	0.073562	0.13731	-0.20211	0.3443
	[CS]	-0.041647	0.19520	-0.42813	0.3361
	[V]	-0.050593	0.57434	-1.26315	0.9854
Complication	[Yes]	0.140114	0.19974	-0.24010	0.5298
Gravidity	[0-3]	-0.059973	0.15274	-0.35068	0.2447
	[4-6]	-0.254560	0.23795	-0.73552	0.2037
Parity	[0-3]	0.077957	0.16884	-0.24276	0.4226
	[4-6]	0.301642	0.28013	-0.24417	0.8546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Density of (Intercept)
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Iterations
Density of Babyweight1
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Trace of MatrnalAge1
Iterations
Density of MatrnalAge1
N = 5000 Bandwidth = 0.031
Trace of MatrnalAge2
Iterations
Density of MatrnalAge2
N = 5000 Bandwidth = 0.04191
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Iterations
Density of FHR
N = 5000 Bandwidth = 0.03341
Trace of Antenatal1
Iterations
Density of Antenatal1
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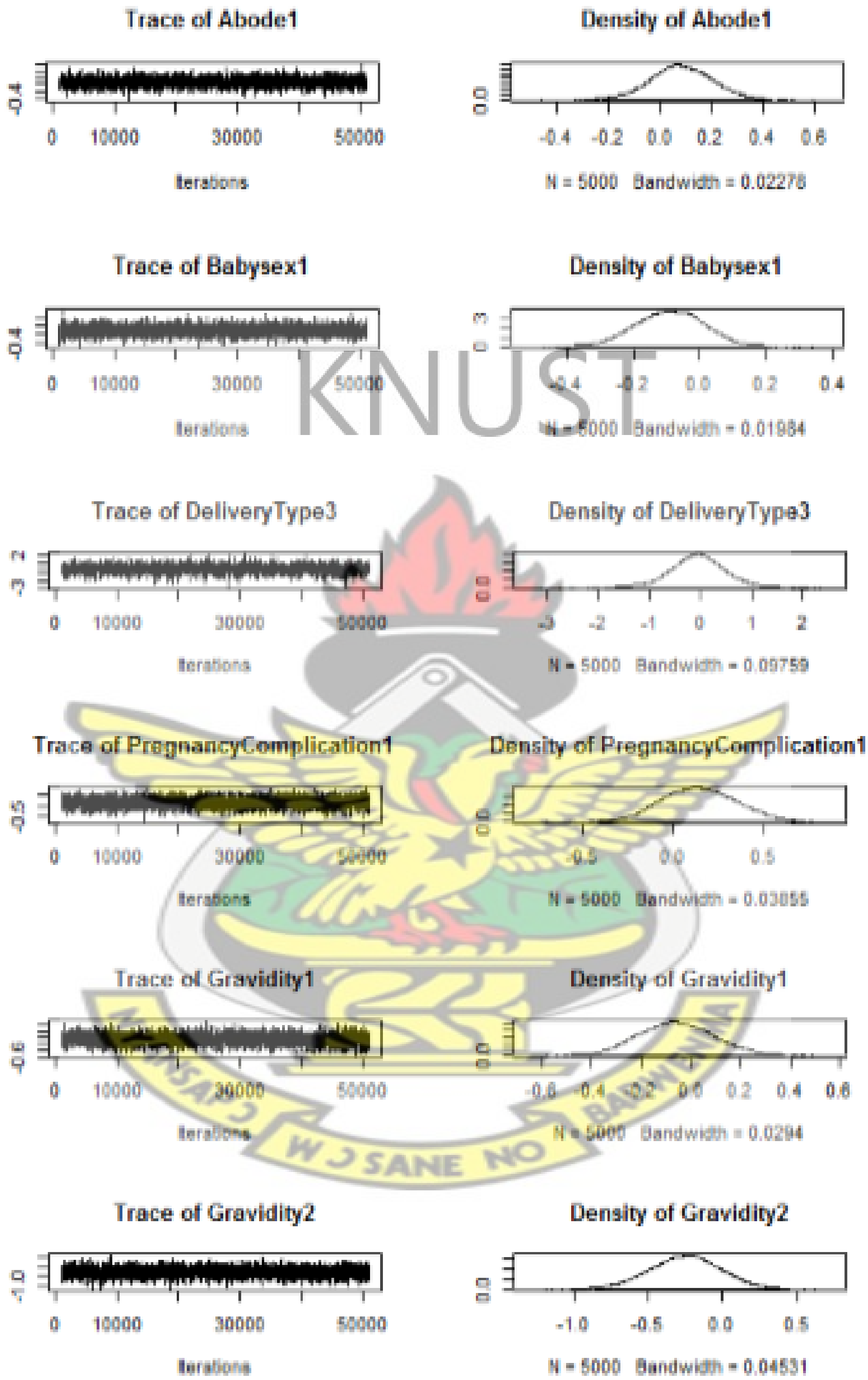
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Iterations
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Iterations
Density of Babysex1
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Iterations
Density of DeliveryType3
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Trace of PregnancyComplication1
Iterations
Density of PregnancyComplication1
N = 5000 Bandwidth = 0.03855
Trace of Gravidity1
Iterations
Density of Gravidity1
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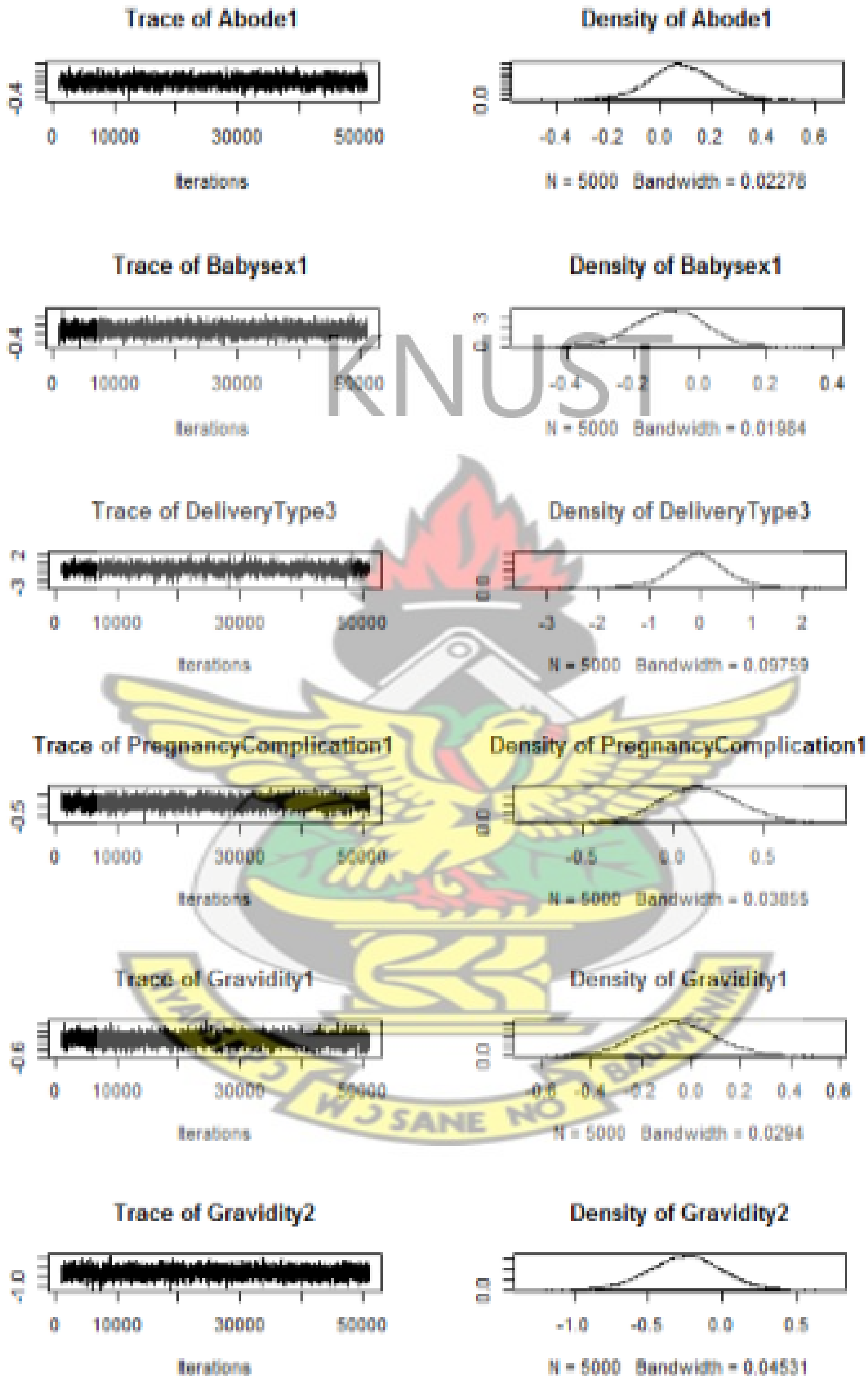
Trace of Gravidity2
Iterations
Density of Gravidity2
N = 5000 Bandwidth = 0.04531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Density of Abode1
Iterations
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Density of Babysex1
Iterations
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Density of DeliveryType3
Iterations
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Trace of PregnancyComplication1
Density of PregnancyComplication1
Iterations
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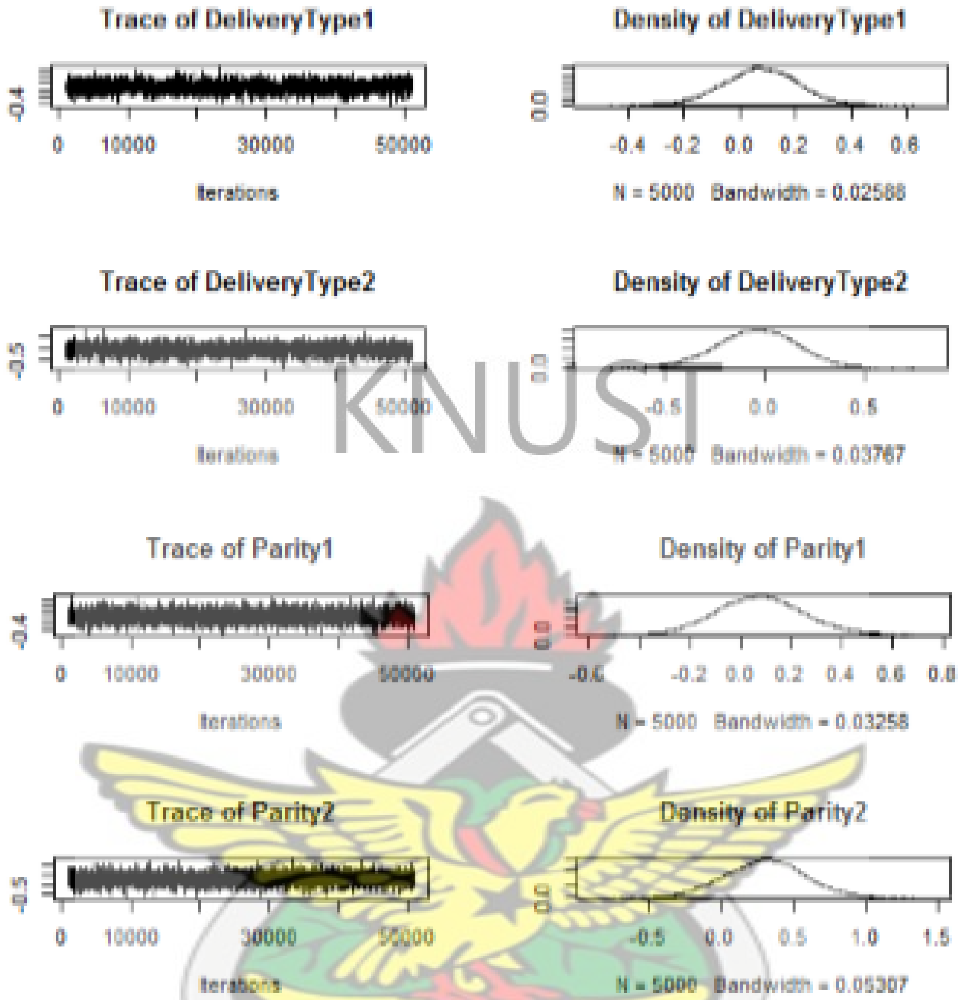


Figure 4.3: Trace and density plot from the Median Quantile Regression ($\tau = 0.50$)

There is general convergence shown from the trace plots (plot of the sample values) of Figure 4.3. Nonetheless, the posterior density plots of the entire predictor variables failed the parallel lines assumptions. This confirms the earlier non-significant contribution of the specified set of predictor variables at the middle or median distribution of the response variable.

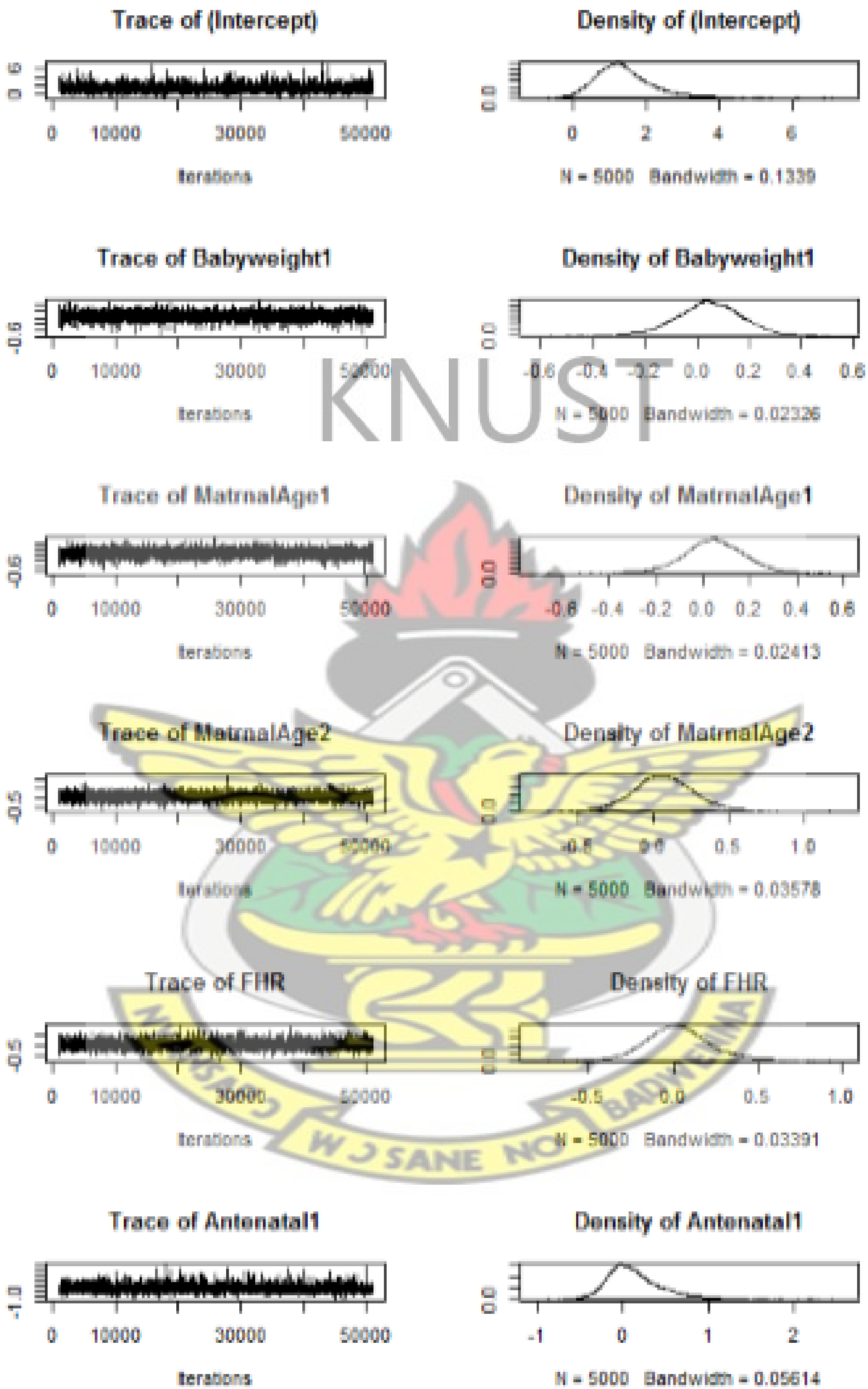
4.6.3 Analysis from the 90^{th} Bayesian Binary Quantile Regression

To specifically examine the behaviour and the associated effects exerted by the predictor or the explanatory variables on the upper-tail of the distribution for the response or outcome variable (term or preterm delivery), the 90^{th} (0.90) binary quantile regression was employed. The Bayesian posterior point estimates and their corresponding Posterior Probability Intervals or Credible Intervals were used to ascertain the influence of each predictor variable on the upper-tail of the outcome variable's distribution.

The results shown in Table 4.6 indicate that, the weight of the newborn, maternal age, estimated blood lost (EBL), fetal heart rate (FHR), APGAR score within the first five (5) minutes, antenatal, intermittent preventive treatment (IPT), place of abode, parity and complication during the pregnancy cycle, exerted positive effects at the upper-tail (90^{th} percentile) of the distribution for the response variable (delivering preterm or term). This means, changes in the identified predictors, causes changes of the same direction for the response variable. Unfortunately, all these positive effects exerted by the aforementioned predictors on the response, were found to have shown non-significant effects. This could be verified from the 95% Credible Intervals; where the lower and upper bounds goes through the zero value. Due to the latter findings, there cannot be any meaningful statistical inference from these predictors.

Table 4.6: Maximum Likelihood Estimates from the Specified Logit Regression

Dependent Variable: Gestation (preterm or term birth)					
Quantile (τ) = 0.90				95% Bayesian Credible Interval	
		Mean	St. Dev	Lower	Upper
Constant		1.4117763	0.81456	0.16209	3.39041
Babyweight	[Below 2.5]	0.0423863	0.12805	-0.23163	0.28166
MaternalAge	[Below 20]	0.0461304	0.13334	-0.23153	0.30897
	[20-30]	0.0672022	0.19049	-0.29794	0.45803
	[31-40]	0.2967074	0.47347	-0.43238	1.42672
EBL	[Below 500]	0.0847283	0.21922	-0.30300	0.57115
APGAR1	[Below 5]	-0.0204497	0.14084	-0.31850	0.22608
APGAR5	[Below 5]	-0.1228091	0.41017	-1.10559	0.52581
FHR	[Below 120]	0.0316678	0.18781	-0.31220	0.43886
Antenatal	[Attended]	0.1593875	0.34561	-0.34737	0.99923
Abode	[Rural]	0.0294302	0.11376	-0.17391	0.27485
Babysex	[Male]	-0.0113373	0.08929	-0.19039	0.16173
Foetus	[multiple]	-0.0807179	0.17249	-0.47181	0.20643
IPT	[No Dose]	0.0060863	0.04191	-0.07832	0.08831
DeliveryType	[CS]	0.0375188	0.15792	-0.23818	0.37772
	[CS]	0.0677291	0.23178	-0.30509	0.62133
	[V]	1.1080052	1.76833	-0.96702	5.80558
Complication	[Yes]	-0.0424091	0.24887	-0.61464	0.37734
Gravidity	[0-3]	-0.0003981	0.13501	-0.26487	0.29004
	[4-6]	-0.0059706	0.23117	-0.44601	0.48455
Parity	[0-3]	0.0235877	0.14903	-0.27206	0.31514
	[4-6]	0.1577929	0.35196	-0.45922	0.95069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Density of Babyweight1
Iterations
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Density of MatrnalAge1
Iterations
N = 5000 Bandwidth = 0.02413
Trace of MatrnalAge2
Density of MatrnalAge2
Iterations
N = 5000 Bandwidth = 0.03578
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Density of FHR
Iterations
N = 5000 Bandwidth = 0.03391
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Iterations
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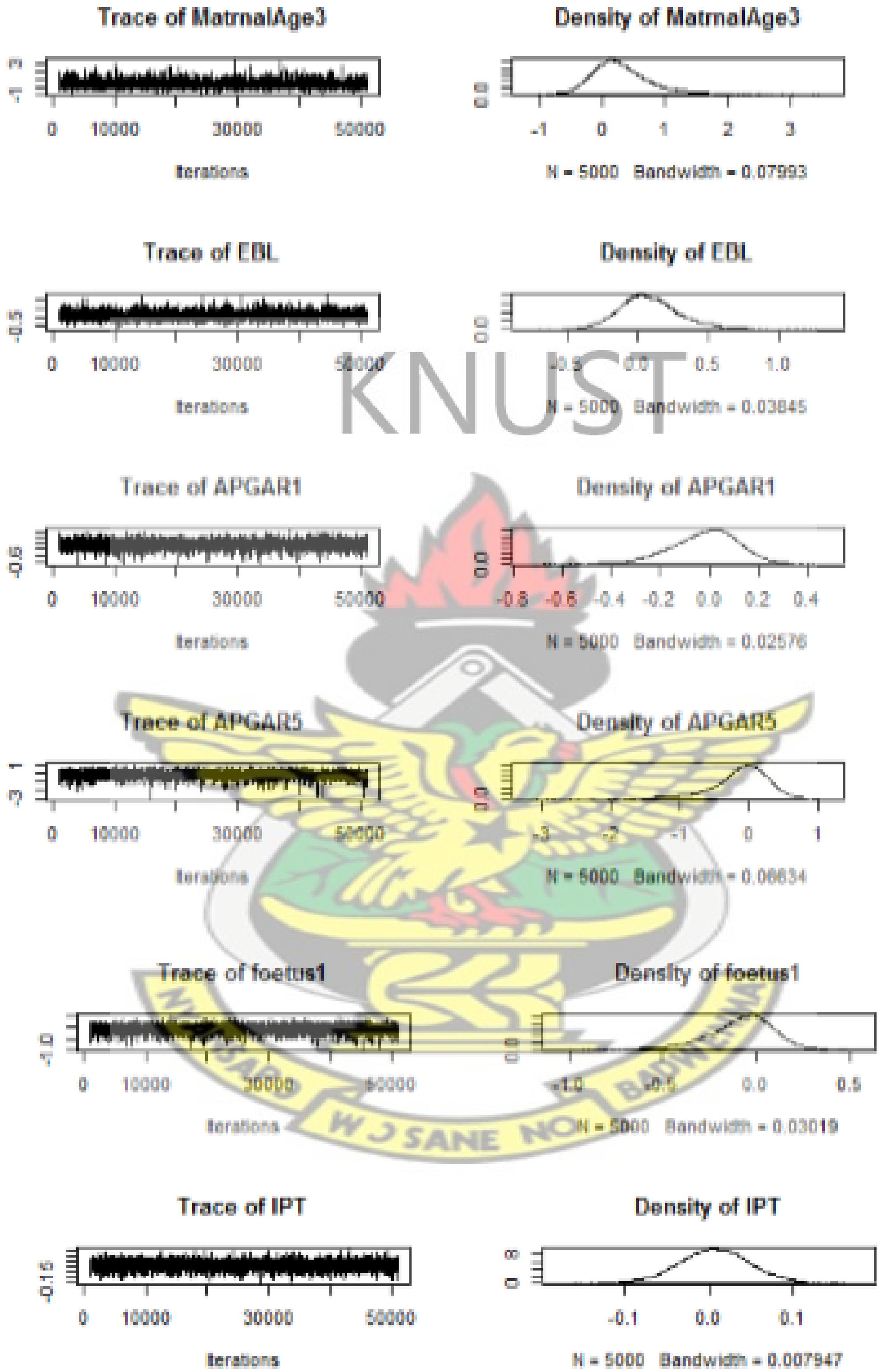
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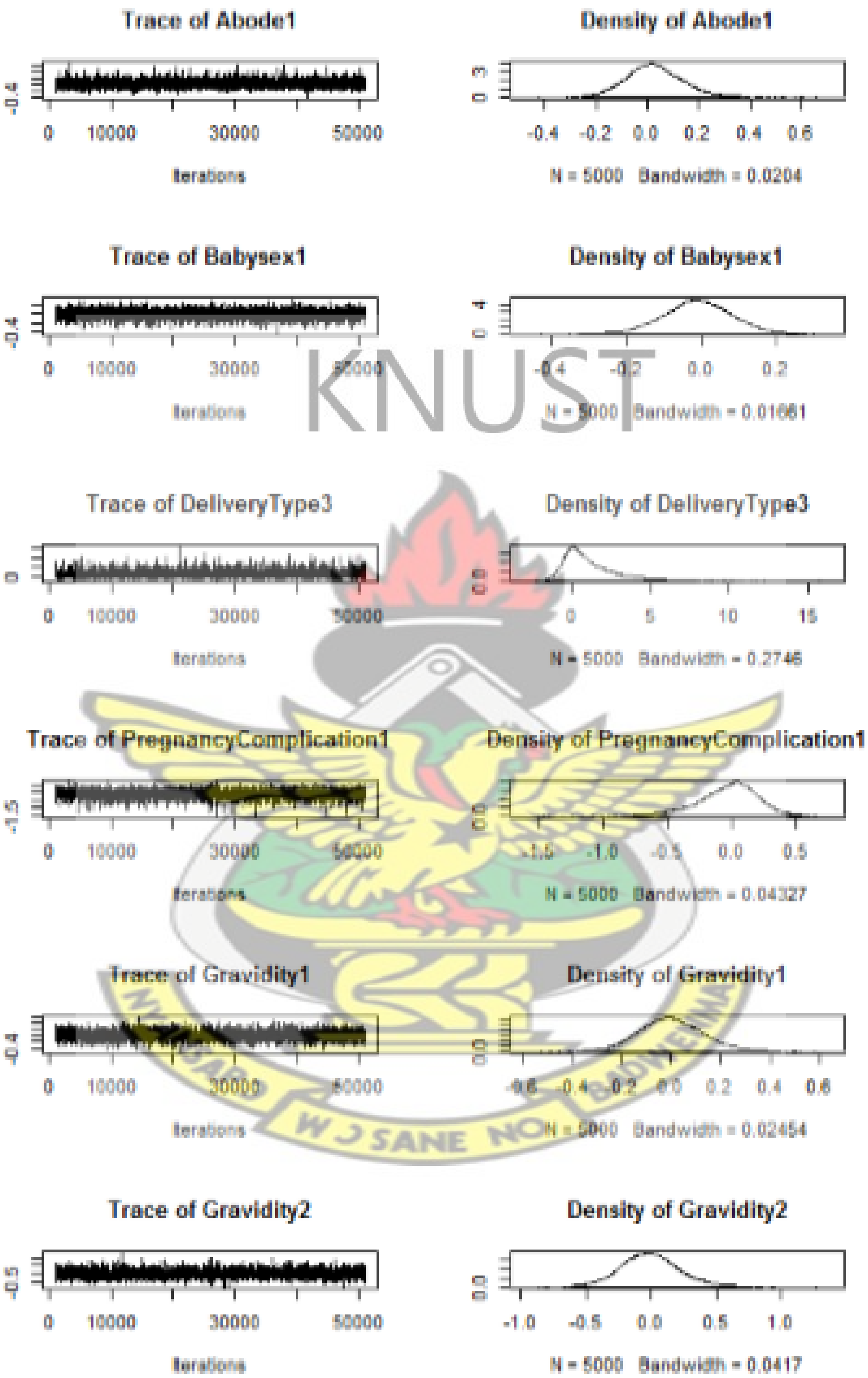
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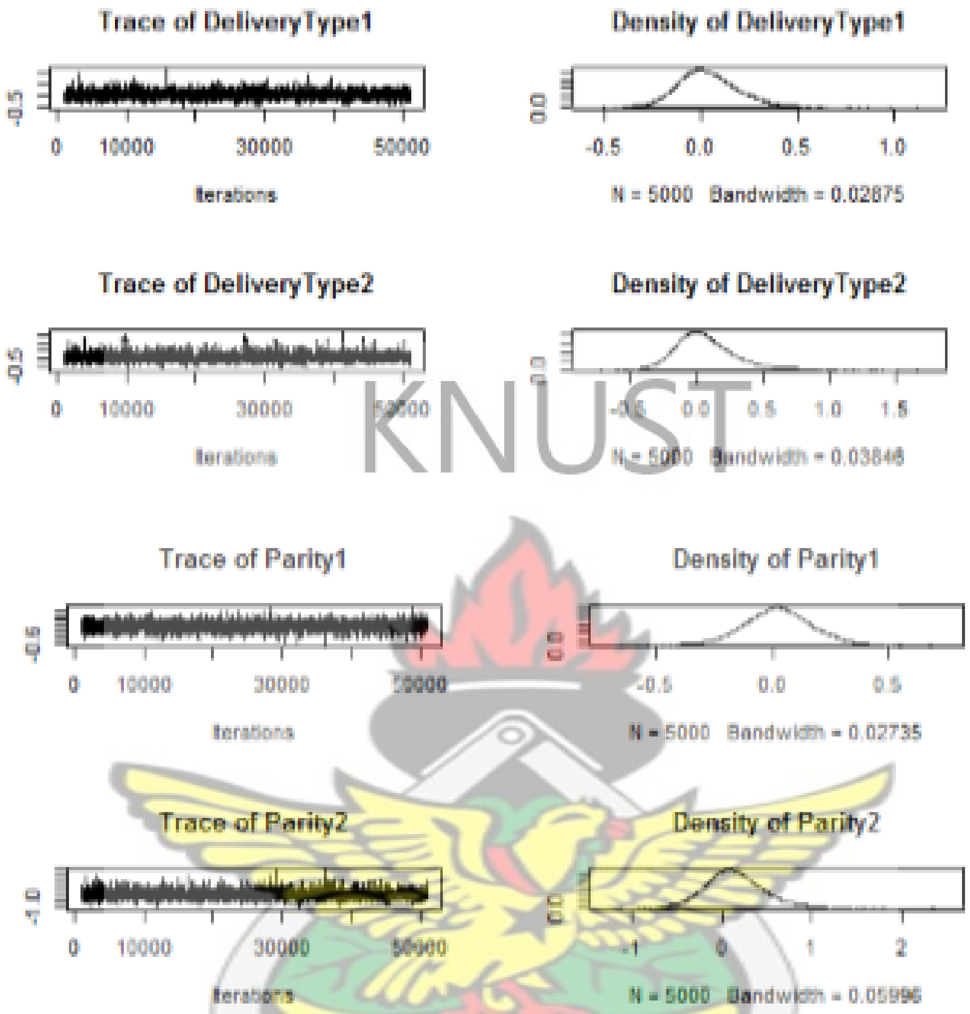

Figure 4.4: Trace and density plot from the Upper Quantile Regression ($\tau = 0.90$)

Generally, the entire trace plots shown in Figure 4.4 oscillate around a stable mean value. This gives indication of convergence at the chosen 50,000 iterations level. Meanwhile, all the posterior density plots for the posterior estimates have their left- and right-tails going through the zero value. This clearly signifies non-conformity with the parallel lines assumption.

Chapter 5

Summary, Recommendation and Conclusion

5.1 Introduction

This last Chapter present summary of findings from the study and gives recommendations to prospective mothers on the identified determinant factors and their associated effects towards delivering babies before term. The Chapter also gives relevant recommendations to healthcare facilities in the entire country. It further ends with a conclusion section which summaries the set objectives against the key findings, and also examined whether such findings are in line with literature.

5.2 Summary of findings from the Study

The main focus of this study was to use binary logistic and quantile regressions to examine determinant factors of preterm births in parts of Ghana; preferably the Administrative District of the Ahafo Ano South. The study also set an objective to assess the prevalence rate of preterm delivery cases in the district. To achieve these targets, the only hospital at the entire district was used as a base for the study. The Mankranso Government Hospital was used as a base for reporting the situation at the district due to its dual purposes. This hospital had been reported in earlier sections of the study to be serving the populace in the district and its catchment areas as readily source of healthcare delivery, and as a referral healthcare point for the few smaller health facilities in the district. This obviously suggests that, data from the hospital would normally represent a fair proportion of health situations in the entire stretch of the Ahafo Ano South District and its immediate envi-

rons. The Hospital-based study made use of retrospective cohort data of delivered mothers and their newborns, obtained from the hospital's Biostatistics Unit. The data used was extracted from the database of the said unit. This extracted data was holistically made up of records taken on pregnant mothers who assessed maternity services at the hospital, and on those who were referred to the hospital for delivery purposes. Altogether, fifteen (15) relevant variables to the study's course were included in the extracted data. These included maternal demographic (age, place of abode), obstetric/delivery characteristics (EBL, antenatal care, number of conceived fetuses, delivery type, pregnancy complication, IPT, gestation period, parity, gravidity) and characteristics of the newborn (baby's sex, APGAR score, fetal heart rate, birth weight).
Under the descriptive analysis, the gestation period (preterm or term) of the delivered mothers was distributed across the other fourteen (14) variables. The counts and associated percentages from this cross tabulation had been reported in the just previous chapter. It was realized from the counts of such cross tabulation that, approximately, every 4 out of 9 live born babies in the Ahafo Ano South District are born before term (preterm born babies). We also realized a fairly high proportion of teenage pregnancy (20.7%) from the entire pregnancy cases considered. Such teenage mothers recorded very high percentage (63.9%) of preterm delivery cases among their cohort. On other key findings, it was revealed to us that majority of the baby's born with low birth weight are more associated with cases involving preterm births. It again revealed that, the lower or average a newborn's APGAR score (out of a maximum of 10 marks), the higher the proportion of such baby to experience preterm delivery.

With respect to the bivariate analysis, the likelihood-ratio chi-square test of association was employed to examine significant association of the response variable, paired with each predictor or independent variable. From the bivariate results, maternal age, number of fetuses conceived to a pregnant mother, intermittent preventive treatment, the newborn's weight, gravidity and parity were statistically significant variables associated with the likelihood of delivery a term or preterm baby. Out of these identified variables, maternal age, the newborn's weight and parity showed stronger association with the response variable of either delivering preterm or term babies. Altogether, these six (6) predictor vari ables were identified as significant determinant factor of the response or outcome variable.

To a further analysis on the multivariate techniques, summary results of the binary logistic and quantile regressions are also reported under this subsection. For the binary logistic regression, four (4) out of the fourteen (14) predictor variables were found to have shown statistical significance. Using the backward selection approach, six (6) of the fourteen predictor variables made it into the final fit. Two (2) of such variables were seen as confounders; whiles the remaining four (4) showed statistical significance. These statistically significant predictors included maternal age, number of conceived fetuses, intermittent preventive treatment and the newborn's weight. With the exception of gravidity and parity, the results of the binary logit fit confirm that of the bivariate technique. Key recaps from the logit analysis indicated that low birth weight babies are highly prone to cases of preterm deliveries. It was also clear that pregnant mothers who conceived multiple fetuses in a pregnant cycle had more tendencies to experience preterm deliveries. Teenage mothers were found to be more susceptible for delivering before term. We again realized that, pregnant mothers who abstained from the intermittent preventive treatment were more likely to be associated with preterm delivery.

On the other side of the multivariate technique, summary reports of the results from the binary quantile regression are outlined under this current subsection. From the Bayesian binary quantile regression, it was unanimously realized that, weight of the newborn, maternal age, intermittent preventive treatment (IPT) and parity, showed positive impacts on the tendency to deliver preterm babies at the lower-, middle- and upper quantiles However, two of these identified predictors, which includes, maternal age and parity, showed significant varying impacts or effects on preterm birth at the lower quantile . In addition, the APGAR score of the newborn within the first five (5) minutes, antenatal, delivery type, parity and complication during the pregnancy cycle were also recorded to have shown varying effects (ie., being it positive or negative) on preterm birth at the specified lower quantile. At the middle or median and upper quantiles, none of the specified predictor variables showed statistically significant effects on preterm birth. This suggests that, for this data, the effects of the predictor variables on the response of either delivering preterm or at term are much felt significantly by the use of the conditional-mean and the lower quantile regressions, rather than examining the effects at the middle/median- and upper- quantiles of the distribution for the response variable.

5.3 Recommendations for Pregnant Mothers

Based on the literature and the empirical findings from the study, we strictly recommend the following measures for pregnant women and other women who have future plans to conceive and give birth to babies:

1. Pregnant women are to at regular times attend antenatal care or seek proper medical care to avoid complications during the pregnancy cycle. This might help boost the health conditions of the fetus, and thereby prevent preterm births which might manifest through a low APGAR score and low weight for the newborn.

2. There is an old adage which says "prevention is better than cure". We strongly recommend pregnant women at the district to prevent the malaria disease by either opting to be placed on the intermittent preventive treatment, or by sleeping under treated mosquito nets, or by generally using several forms of mosquito repellents (repellent creams, mosquito coils, mosquito sprays, mosquito bulbs, etc.).

3. Teenage pregnant mothers are reported by this study as being more susceptible to preterm deliveries; we therefore recommend such mothers to seek early medical attention and to follow all instructions given them at the antenatal units.

4. Pregnant mothers whose status have been revealed to them of conceiving more than one fetuses in a single pregnancy should at regular times seek antenatal care or should arrange to be put on special medical care to avoid preterm deliveries.

5. It was reported from the study's findings that, mothers with record of low parity are more vulnerable to experiencing preterm births. Due to this unfortunate finding, we again recommend first-time mothers, or mothers with lower number of births to seek proper medical care during another pregnancy cycle, to reduce the risk of preterm delivery.

5.4 Recommendations for Health Administrators

From the analysis and key findings from the study, we again recommend Health Administrators and maternity healthcare facilities to consider the following remedies:

1. It was realized that, even some of the delivered mothers who seek antenatal services were victims of preterm deliveries; we by this recommend that the antenatal unit of the hospital and other smaller facilities in the district should intensify their antenatal activities to help bring to barest minimum, cases of preterm births at the district.

2. Smaller healthcare facilities (clinics, health centers, ect.) in the Ahafo Ano South District must as early as possible refer pregnant mothers who accesses maternity services at their units, to the only hospital at the district if initial care is beyond their control.

3. Teenage pregnancy is at its ascendency in the district; we recommend the Reproductive and Child Health Unit at the district to intensify education on effective use of

modern contraceptives, or if possible, disseminate much information on abstinence practices to prevent teenage pregnancies and its associated risks such as preterm births.

5.5 Conclusion

This study was aimed at examining the prevalence rate of preterm births and assessing determinant factors of pregnant mothers who delivered live born babies before term at the Ahafo Ano South District. Generally, it was found that, approximately, every 4 out of 9 recorded live birth cases at the district was associated with preterm birth (preterm delivery). In all the aggregated results obtained, it was revealed to us that, maternal age, baby's weight, number of fetuses conceived by a pregnant mother, intermittent preventive treatment, gravidity and parity, were statistically significant predictive factors that contribute to the response variable of being born preterm or at term. Other equally significant variables on the response variable include, the APGAR score of the newborn within the first five minutes, antenatal, delivery type and complication during the pregnancy cycle. With the exception of the intermittent preventive treatment (IPT) and the APGAR score, all the identified predictive factors conform to other works reviewed under the literature subsection of the second chapter. This suggests that, this current study through its findings have identified, yet, other pair of predictive factors that determines the likelihood of being born preterm or at term. We again found out from the multivariate analyses at the lower quantile ($\tau = 0.05$) that, a pregnant woman's decision to attend or not to attend antenatal services was significant in determining whether she delivered preterm or at term. Moreover, the descriptive analysis showed that, a manageable proportion (52.8%) of pregnant mothers who attended antenatal sections, at least once, delivered at term. This still recount the importance of antenatal services to term delivery. These findings together answer successfully the set objectives and research questions of this study.

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