

Original Research Article

Bayesian and frequentist comparison: An application to Low Birth Weight babies in Ghana

Abstract

The aim of this study is to evaluate the association between maternal factors and birth weight among babies by using and comparing frequentist and Bayesian methods' results from an epidemiologist or public health point of view. Low birth weight babies, defined by WHO as babies born at term who weigh less than 2.5kg is an important indicator of reproductive health and general health status of any Population. The incidence of low birth weight is quite high in the sub region which has a public health concern.

The study used a data set based on Multiple Indicators Cluster Survey conducted by Ghana Statistical Service in 2011 to monitor progress of women and children. A sample of 10,963 women within the reproductive age (15 – 49) years across the country between 2009 and 2011 were selected for the survey.

The results from the frequentist and the Bayesian models show that, the two approaches can yield similar results using same data set. However, there are factors that the Bayesian technique can unfold which might not be the case using the frequentist model. We were able to show that the Bayesian approach may have advantages over the frequentist one, particularly with respect to our data. The use of informative priors might however be useful in narrowing credible interval and providing precise choice between the null and alternative hypothesis. In case of borderline frequentist results, the Markov Chain Monte Carlo method may be more conservative, particularly without priors.

Comparing the two approaches with respect to our data set, we can infer (from table 4) that using Bayesian model provides better estimates in predicting low birth weight among babies in Ghana. We note however that to better understand the phenomenon under study the two methods should be used together. Our findings further revealed that low birth weight is not only a public health problem but also a socio-cultural issue.

Keywords: low birth weight, frequentist, Bayesian, informative priors

1. Introduction

The debate over Bayesian versus Frequentist statistical inference is largely over in statistics community. Both Bayesian and frequentist ideas have a lot to offer practitioners. Each approach has a great deal to contribute to statistical analysis and each is essential for the full development of the other approach. Both methods often lead to the same solution when no external information (other than the data and the model itself) is introduced into the analysis. But these methods are not the same and do different things. It is very important to understand the assumptions behind the theories and to correctly interpret the mathematical conclusions produced. Using both approaches for an important problem is good in practice (Badu GJ, 2006). The union of frequentist and Bayesian procedures is discussed extensively by Bayarri and Berger (2004), and this study is based partly on their work. Statistical frequentist

40 techniques are sometimes misinterpreted or misused, while Bayesian techniques seem to
41 present several practical advantages, such as accommodating small sample sizes, unobserved
42 variables along with measurement errors and incorporating information from previous studies
43 (Pascale Salameh et al 2014).

44 In general, frequentist methods are computationally relatively simple. There is no need for
45 numerical integration. Many of these methods, for sufficiently large data sets, are the locally
46 most powerful tests possible. In many cases the frequentist and Bayesian interpretations are
47 different: Bayesian methods are based on *decision theoretic principles*; actions are dictated
48 by risk management by minimising the expected loss under a chosen ‘loss’ function. Similar
49 choices are needed in frequentist methodology to determine the optimal procedure (e.g. least
50 squares or maximum likelihood estimation).

51 Frequentist principle is based on the idea that, with repeated use of a statistical procedure, the
52 actual accuracy of the long run average should not be less than the reported accuracy of the
53 long average. This is really a joint frequency-Bayesian principle.

54 Low birth weight (LBW) is one of the key reproductive health indicators whose outcome is
55 influenced by consumption of reproductive health care. Rosenzweig and Schultz (1983) argue
56 that one of the key measures of child health is that of birth weight. Birth weight is a good
57 gauge of health of the child in the womb because the weight is taken immediately after birth.
58 Consequently, a malnourished fetus will be born at low birth weight. Growth of the fetus is
59 affected by maternal, environmental and genetic factors. Intrauterine growth and
60 development is one of the most vulnerable processes in human life cycle and its aberrations
61 can result in lasting profound influence in later life. In the context of developing countries,
62 intrauterine growth has been invariably assessed by birth weight (Sachdev H.P.S. 2001). The
63 birth weight of an infant is the single most significant determinant of its chances of survival,
64 healthy growth and development (Park K. 2007).

65 LBW is prevalent in developing countries especially those in the Sub-Saharan region due to
66 the high levels of malnutrition and infectious diseases. Globally, more than 20 million infants
67 are born with low birth weight. The number of low birth weight babies is concentrated in two
68 regions of the developing world: Asia and Africa. 72% of low birth weight infants in
69 developing countries are born in Asia where most births also take place, and 22% are born in
70 Africa. India alone accounts for 40% of low birth weight births in Asia with countries in the
71 western world such as Sweden is between 4% and 6% (UNICEF 2003).

72 A child’s birth weight is an important indicator of the child’s vulnerability to the risk of
73 childhood illnesses and the chances of survival. Sub-Saharan Africa (SSA) has the second
74 highest incidence of low birth weight infants the world over (16%), with South Central Asia
75 being the highest at 27% (UNICEF and WHO 2004). The most recent evidence in Ghana
76 shows that approximately 10% of all births are LBW (GSS, 2009). In particular, the UN
77 envisages a reduction of low birth weight by at least one-third in the proportion of infants.
78 This target is in fact, one of the seven major goals for the current decade of the “A World Fit
79 for Children” programme of the United Nations (UN, 2004).

80 The prevalence of LBW situation in Ghana is not so different from what pertains in the sub
81 region. The rate has been hovering around 10% according to the various results contained in
82 the Multiple Indicators Cluster Questionnaire Surveys (MICS) and the Demographic and
83 Health Surveys (DHS) conducted over the years. This includes only a few babies who are
84 weighed at birth or described as being “very small” or “smaller than average” when born. The
85 major challenge is that most babies born in Ghana are not weighed at birth due to the fact that
86 most mothers give at home and not at health facilities. For instance, about 79% of babies born
87 in were not weighed according to the 1998 DHS report (page; 98). Again, in the 2003 DHS
88 information on birth weight was known for only 28% babies in the five years preceding the
89 survey and for the 2008 DHS, birth weight was reported for only 43% of births in the five
90 years preceding the survey. The 2006 MICS report also indicates that, overall, nearly 2 in 5
91 babies are not weighed at birth and approximately 9% of infants are estimated to weigh less
92 than 2.5 kg at birth. However, some research findings at various facilities across the country
93 put the prevalence rate above 16% which is higher than the 15% global average threshold
94 making it a public health concern as a country. Again, according to the WHO data published
95 in April 2011 LBW deaths in Ghana reached 6,056 or 3.23% of total deaths in the country.
96 Currently LBW is among the top 20 causes of deaths in Ghana.

97 The primary objective of our present study is to evaluate the association between maternal
98 factors and birth weight among babies by using and comparing frequentist (both Fisherian
99 and Neyman-Pearson approaches) and Bayesian methods’ results from an epidemiologist or
100 public health point of view.

101 The justification for the comparison of Bayesian and Frequentist in this study is based on
102 *coherence* and *calibration*. These are two important goals for statistical inference;

- 103 i. Bayesian work has tendered to focus on coherence whilst Frequentist work has not
104 been too worried about coherence. The problem with pure coherence is that one
105 can be coherent and completely wrong.
- 106 ii. Frequentist work on the other hand tends to focus on calibration whilst Bayesian
107 work has not been too worried about calibration. The problem with pure
108 calibration is that one can be calibrated and completely useless.

109 Many statisticians therefore make use of both Bayesian perspective and Frequentist
110 perspective, because a blend is often a natural way to achieve both coherent and
111 calibration.

112 1.1 Conceptual Framework

113 Reasons for choosing to compare these approaches’ results are numerous, namely because
114 frequentist techniques, although the most universally used, are sometimes considered as
115 misinterpreted or misused (Greenland S 2006; Goodman S. 1999; Spiegelhalter DJ et 2004),
116 while Bayesian techniques are underused while they seem to present several practical
117 advantages, such as accommodating small sample sizes, missing data, covariates measured
118 with error, random effects or a hierarchical structure of variables, unobserved variables along
119 with measurement errors and incorporating information from previous studies (Greenland S.
120 2006; Goodman S 1999; Spiegelhalter DJ et al 2004; Dunson D. 2001).

Bayesian methods are defined as the explicit quantitative use of external evidence in the design, monitoring, analysis, interpretation and reporting of a study [Dunson D. 2001]. Results of epidemiological observational studies provide a likelihood that can be combined with prior information using standard and advanced full Bayesian methods (Spiegelhalter DJ et al 2004), leading to purely probabilistic results. The specific application of Bayesian methods to case-control studies is both feasible and useful, particularly with the advance of advanced computational methods (Marshall RJ 1988; Zelen M, Parker RA 1986): with the advent of Markov Chain Monte Carlo (MCMC) methods, Bayesian methods are being implemented with increasing frequency. MCMC methods are computer-intensive technical methods that allow one to simulate draws from the posterior distribution, without having to calculate the posterior distribution (Gilks WR et al 1996).

Moreover, in parallel to the classical confidence interval, Bayesian methods offer what is called the Bayesian credible interval; it has a simple appealing interpretation as the interval containing the true parameter of interest with some probability (e.g., 95%). Most researchers prefer this easy interpretation to that of the classical 95% confidence interval, which is the range of values containing the true parameter 95% of the times in repeated sampling (El-Hakim IE, Uthman MA 1999); furthermore, people sometimes wrongly interpret the confidence interval as if it was a credible interval. In this sense, Bayesian approach seems more intuitive.

Although these practical advantages have long been presented for epidemiologists, few epidemiological studies have used this powerful tool to assess exposure-disease relations (El-Hakim IE, Uthman MA 1999). Controversies are raised by the Bayesian approach, since it forces one to re-examine fundamental notions about the concept of probability and classical statistical practices (Etzioni R, Kadane J 1995): its usefulness is accepted in specific situations such as in case of sequential data, but its system of inference using priors in other situations is still controversial (Etzioni R, Kadane J 1995) because it is considered subjective (Greenland S 2006). Thus, comparing results, interpretations and limitations of both approaches would enrich our discussion and make our conclusions more robust.

2. Data

The 2011 Multiple Indicator Cluster Survey (MICS) data was used in this study. This is a fourth round of the survey which is conducted every five years to monitor the situation of children and women in Ghana. In this survey about 10,963 women who were within the reproductive age (15 – 49 years) were selected across the ten Regions of Ghana. The subjects were interviewed reference to two years preceding the survey. The selection procedure was based on a representative probability sample of households nationwide from a frame of Ghana 2010 Population and Housing Census Enumeration Areas (EA's). For comparability, the MICS used an internationally standardized sampling of two-stage stratified sample design. At the first stage, a number of EA's were selected from the regions which were considered as clusters. The households in each region were then selected using systematic sampling with probability proportional to size in the second stage. Of the 12,150 households

selected for the sample, 11, 925 households were contacted and duly interviewed. In the households interviewed, 10,963 women aged 15 – 49 years were identified for interview

3. Methodology

The 2011 MICS was carried out on a sample of 11,925 households from a selected household of 11,970 in all the ten administrative regions of Ghana giving about 100% response rate. The households were selected due to the sizes of the regions. The survey used both qualitative and quantitative methods of data collection aimed at providing basic data for measuring the progress of children and women in the country. Data used for analysis in this paper was based on information on all births and deaths that had occurred two years prior to the survey period. Statistical package for social scientists (SPSS version 20), R-console and SAS system version 9.4 were used for extraction and the eventual analysis of data. Descriptive statistics and frequencies of the background characteristics of the mothers and the respective households the children belong to were generated. The association between the independent and dependent variable was established using chi-square analysis procedures. The dependent variable selected was the outcome of the weight of the baby whether normal or LBW. The independent variables included children ever born, ethnicity, area of residence, antenatal care, region, economic status and mothers' characteristics including; education, religion and age. A critical level of significance of 5 percent ($p < 0.05$) was used to identify the most statistically significant determinants of LBW babies. Estimates of LBW were obtained for the overall study regions.

3.1 Model Specification (logistic regression)

The following generalized linear logistic model was used

$$\pi = \log \left(\frac{u}{1-u} \right) = \chi\beta + \varepsilon \quad (1)$$

where π links the linear function to $\log \left(\frac{u}{1-u} \right)$. The link is not a linear function, μ is the probability of having a LBW baby and χ is the model matrix including antenatal care, mothers' educational level, age, ethnicity, religion, economic status of household and parity. The matrix also includes geographical location, such as region of origin and whether the respondent is from rural or urban environment; β is the vector of parameters, and ε is the vector of residuals. The Fisher scoring method was applied (SAS, 2007) to obtain Maximum Likelihood estimates of β . The overall goodness of fit is derived from the Likelihood Ratio Test of the hypothesis $H_0: c(\beta) = 0$ where a comparison is made between the full model and the model that contains only the intercept (Hilbe and Greene, 2008). Therefore, it is a test for global null hypothesis of the elements of the solution vector.

The odds ratio in this study is the probability that a child will be born of LBW to the probability that the child born has normal birth weight. This means that the outcome variables in the logistic regression should be discrete and dichotomous. Logistic regression was found fit to be used because the outcome variable was in binary form that is a child is born with LBW or otherwise. In addition, there were no assumptions to be made about the distributions of the explanatory variables as they did not have to be linear or equal in variance within the

group. The model suggests that the likelihood of a woman giving birth to a LBW child varies across all the independent variables to be studied. After fitting the model, the outcomes were used to interpret the existing relationships between LBW babies, household structure and mothers' characteristics.

3.2 Markov chain Monte Carlo

In general, the posterior distribution, or any of its summary measures, can only be obtained analytically for a restricted set of relatively simple models. Thus, for a long time, researchers could only proceed easily with Bayesian inference when the posterior was available in closed-form or as a (possibly approximate) analytic expression. As a result, practitioners interested in models of realistic complexity did not much use Bayesian inference. This situation changed dramatically with the advent of computer-driven sampling methodology, generally known as Markov chain Monte Carlo (MCMC: e.g., Gamerman & Lopes, 2006; Gilks, Richardson, & Spiegelhalter, 1996). Using MCMC techniques such as Gibbs sampling or the Metropolis–Hastings algorithm, researchers can directly sample sequences of values from the posterior distribution of interest, forgoing the need for closed-form analytic solutions. The current adage is that *Bayesian models are limited only by the user's imagination*.

3.2.1 Gibbs Sampling

The formal algorithm can be specified as follows. Let θ be a vector of model parameters with elements $\theta = \{\theta_1, \dots, \theta_q\}$. The elements of θ could be the parameters of a regression model, structural equation model, and so forth. Note that information regarding θ is contained in the prior distribution $p(\theta)$. A number of algorithms and software programs are available to conduct MCMC sampling. Following the description given in Gilks et al. (1996), the Gibbs sampler begins with an initial set of starting values for the parameters, denoted as

$\theta^{(0)} = (\theta_1^{(0)}, \dots, \theta_q^{(0)})$. Given this starting point, the Gibbs sampler generates $\theta^{(s)}$ from $\theta^{(s+1)}$ as follows:

1. sample $\theta_1^{(s)} \sim p(\theta_1 | \theta_2^{(s-1)}, \theta_3^{(s-1)}, \dots, \theta_q^{(s-1)}, y)$

2. sample $\theta_2^{(s)} \sim p(\theta_2 | \theta_1^{(s-1)}, \theta_3^{(s-1)}, \dots, \theta_q^{(s-1)}, y)$

- q sample $\theta_q^{(s)} \sim p(\theta_q | \theta_1^{(s-1)}, \theta_3^{(s-1)}, \dots, \theta_{q-1}^{(s-1)}, y)$

Then, a sequence of dependent vectors are formed:

$$\theta^{(1)} = (\theta_1^{(1)}, \dots, \theta_q^{(1)})$$

$$\theta^{(2)} = (\theta_1^{(2)}, \dots, \theta_q^{(2)})$$

$$\theta^{(s)} = (\theta_1^{(s)}, \dots, \theta_q^{(s)})$$

This sequence exhibits the so-called *Markov property* insofar as $\theta^{(s)}$ is conditionally independent of $\{\theta_1^{(0)}, \dots, \theta_q^{(s-2)}\}$ given $\theta^{(s-1)}$. Under some general conditions, the sampling distribution resulting from this sequence will converge to the target distribution as $s \rightarrow \infty$. See Gilks et al. (1996) for additional details on the properties of MCMC. In setting up the Gibbs sampler, a decision must be made regarding the number of Markov chains to be generated, as well as the number of iterations of the sampler. With regard to the number of chains to be generated, it is not uncommon to specify multiple chains. Each chain samples from another location of the posterior distribution based on purposefully dispersed starting values. With multiple chains, it may be the case that fewer iterations are required, particularly if there is evidence for the chains converging to the same posterior mean for each parameter. In some cases, the same result can be obtained from one chain, although often requiring a considerably larger number of iterations. Once the chain has stabilized, the iterations prior to the stabilization (referred to as the *burn-in* phase) are discarded. Summary statistics, including the posterior mean, mode, standard deviation, and credibility intervals, are calculated on the post-burn-in iterations. Also, convergence diagnostics are obtained on the entire chain or on post-burn-in iterations.

The Bayesian analysis was performed using models identical to those used in the frequentist analyses. Non informative priors were used in this study. The MCMC method was then applied to derive posterior distributions of the model parameters, using SAS 9.4 and R-Console statistical software packages. Means, 95% credible intervals, and probability of the odds ratios were presented. We also indicatively presented the Deviance Information Criterion, a model goodness of fit measure that usually allows comparing models on the same data set: a lower DIC generally indicates a model that fits better to data (Spiegelhalter DJ 2002). Interpretation of both frequentist and Bayesian analyses were presented, stressing on differences, similarities and complementarities between both methods

4. Results

There were 2873 births registered within the survey period. Out of this figure, 1336 were weighed at birth which is about 46.5%. The LBW prevalence in this study was 13.7% (from our sample of non-missing weights). Table 1 provides a descriptive view of the different categories. Five regions; Western, Volta, Greater Accra, Brong Ahafo and Eastern all recorded rates lower than the national figure of 13.7%. Women from Central region are more likely to give birth to low birth weight children (about 16%) and those from Western and Volta regions the least likely to give birth to low birth weight children (4.4%). Low birth weight is also predominant among children born in the three northern regions of the country. Women from rural households, those from the poorest households and those who have a maximum of middle school education are more likely than more advantaged women to give birth to children of low birth weight. For example, the proportion of low birth weight among women who have a maximum of middle school education is 76.1%, compared to 23.9% of women who have a minimum of secondary school education. Women in rural households are likely to give birth to children of low birth weight compared to those in urban households. Women from wealthiest households are more likely to give birth to normal weight children compared to children from poorest households. The possibility of giving birth to children of low birth weight among first time mothers and those who have at least four children is higher than second time mothers. Again, women who are at most 24 years or above 35 years have

highest proportion of children weighing less than 2.5 kg. Tables 2 and 3 depict the results of multivariate logistic analysis and Bayesian results of maternal factors associated with LBW. The factors observed to be highly significantly associated with LBW included maternal age and children ever born (parity) with parity 8 being highly significant. The Bayesian model also show some significance in ANC. The results from (figure 1) also show the density plots and the trace plots for the parameters. The density plots portray the credible intervals of the parameters and the trace plots were used to test the convergence of the model (MCMC). From the figure, it is clear that antenatal care, age squared and parity especially parity eight all passed the convergence test, giving credence to the models' validity.

Table 4 shows the results of both frequentist and Bayesian models. We compared the two results based on the odds ratio, standard errors and credible intervals/confidence intervals. From the table, the odds ratio that fall within the Confidence intervals also fall in the Credible intervals. Generally however, the odds ratio in the Bayesian are higher than that of the frequentist especially where the parameters are significant. The standard errors in the Bayesian model are also lower compared with the frequentist model. This means that the Bayesian model can be more relied upon than the frequentist model. The credible intervals appear to be more spread than the confidence limits.

5. Discussion

The 13.7% prevalence of low birth weight (mean = 2.105 ± 0.031) and the normal mean birth weight of 4.012 ± 0.062 kg observed in this study is comparable to other studies in the developing world (e.g., Nigeria, which is about 14%). The missing link is that few mothers in Ghana give birth at health facilities and hence their babies are not weighed at birth. About 46.5% of the children who were born in the survey period were weighed at birth (1336 of the 2873 births). The descriptive statistics show that residence (locality) has impact on the weight of the new born. Mothers in rural areas tend to give birth to low birth weight children than women who live in urban areas. This is also evidenced by (Deshmukh et al. 1998; Stephenson and Symons, 2002; UNICEF, 2003; Torres-Arreola et al. 2005; Negi, et al. 2006, Khatun and Rahman, 2008). More so a case control study by (Nagargoje M.M, Chaudhary S.S, Deshmukh T.S, Gupta S.C and Misra S.K. 2010; 2011) to determine the risk factors for LBW in Nagpur city of Maharashtra also found place of residence (rural) to be associated with LBW.

The factors found to be significant using the frequentist models include age and parity. All the other variables like residence, ANC, Region, educational levels and economic status were not significant. This is similar to results obtained by (Hogan D.P et al 2000 and Bategeka et al. 2009) whose work revealed educational levels as not being a risk factor in predicting low birth weight. The findings however, is in sharp contrast to (Sachin S.M, Girish M, Rajesh D, Surekha Y, Madhav K.T and Kiran P. 2011) who found both age and parity not to be significant to low birth weight in their study of a number of maternal factors including; birth spacing, height, pre-delivery weight and pregnancy weight gain, age, parity, educational level, economic status, ANC, maternal exposure to tobacco and hypertension anaemic.

The Bayesian model on the other hand using same variables as the frequentist model produced age, parity and ANC to be risk factors associated with low birth weight. Again, all the other factors like residence, Region and educational levels considered in the model are

not significant. This stands to reason that using Bayesian approach may unveil additional risk factor(s) in predicting low birth weight which might not come out clearly when using the frequentist approach. However the high risk for mothers bearing their eighth child found from both models must be a source of worry.

Comparing the two models we find that the errors associated with the Bayesian model are much lower than the frequentist model; an indication that the Bayesian model may predict better even with non informative priors. This corroborates with the study conducted by Pascale et al in 2014 who also in comparing the two methods found the Bayesian to perform better.

6. Conclusion

The results from the frequentist and the Bayesian models show that, the two approaches can yield similar results using same data set. However, there are factors that the Bayesian technique can unfold which might not be the case using the frequentist model. With respect to our data set, using the Stepwise approach for the classical methods, antenatal care (ANC) was never found to be significant yet it came out clearly as one of the significant factors in the Bayesian analysis. This stands to reason that the Bayesian models could reveal something that the usual frequentist models could not. We were able to show that the Bayesian approach may have advantages over the frequentist one, particularly with respect to our data. The use of informative priors might however be useful in narrowing credible interval and providing precise choice between the null and alternative hypothesis. In case of borderline frequentist results, the MCMC method may be more conservative, particularly without priors.

Comparing the two approaches with respect to our data set, we can infer (from table 4) that using Bayesian model provides better estimates in predicting LBW among babies in Ghana. We note however that to better understand the phenomenon under study the two methods should be used together. Our findings further revealed that LBW is not only a public health problem but also a socio-cultural issue.

The results of this study suggest that for reducing LBW, the strategy needs to focus attention on nutrition education to facilitate better weight gain during pregnancy focusing more on the girl-child education, regular antenatal care visits and discouraging teenage and old age pregnancy, bearing more children as well as formulating policies that will reduce poverty among rural women. The girl child education policy must also be given all the needed resources it requires to achieve the desired set targets.

363 Table 1 Descriptive characteristics of the study population

Indicator	LBW (< 2.5 kg)	Normal (≥ 2.5 kg)	Total
	N (%)	N (%)	N (%)
Baby's weight			
	183 (13.7)	1153 (86.3)	1336 (100)
Mothers Age			
≤24	55 (4.1)	232 (17.4)	287 (21.3)
25 – 34	88 (6.5)	609 (45.6)	697 (52.1)
35+	40 (2.8)	312 (23.2)	352 (26.0)
Total	183 (13.7)	1153 (86.4)	1336 (100)
Antenatal care			
Attended	182 (13.6)	1147 (85.9)	1329 (99.5)
Not attended	1 (0.1)	6 (0.4)	7 (0.5)
Total	183 (13.7)	1153 (86.3)	1336 (100)
Area/location			
Urban	85 (6.4)	511 (38.2)	569 (44.6)
Rural	98 (7.3)	642 (48.1)	740 (55.4)
Total	183 (13.7)	1153 (86.3)	1336 (100)
Children ever born			
1	65 (4.9)	246 (18.4)	311 (23.3)
2	34 (2.5)	199 (14.9)	233 (17.4)
3	29 (2.2)	203 (15.2)	232 (17.4)
≥4	55 (4.1)	504 (37.9)	559 (42.0)
Total	183 (13.7)	1153 (86.3)	1336 (100)
Wealth index quintiles (Economic status)			
Poorest	46 (3.4)	319 (23.9)	365 (27.3)
Second	35 (2.6)	229 (17.1)	264 (19.8)

Middle	40 (3.0)	185 (13.8)	225 (16.8)
Fourth	34 (2.5)	209 (15.6)	243 (18.2)
Richest	28 (2.1)	211 (15.8)	239 (17.9)
Total	183 (13.7)	1153 (86.3)	1336 (100)
Mother's education			
Pre school	0 (0.0)	2 (0.2)	2 (0.2)
Primary	44 (4.9)	227 (25.4)	271 (30.3)
Middle	64 (7.2)	347 (38.8)	411 (46.0)
Secondary+	34 (3.8)	176 (19.6)	210 (23.4)
Total	142 (15.9)	752 (84.1)	894 (100)
Region			
Western	8 (0.6)	81 (6.1)	89 (6.7)
Central	30 (2.2)	161 (12.1)	191 (14.3)
Greater Accra	14 (1.0)	123 (9.2)	137 (10.3)
Volta	8 (0.6)	64 (4.8)	72 (5.4)
Eastern	11 (0.8)	75 (5.6)	86 (6.4)
Ashanti	19 (1.4)	96 (7.2)	115 (8.6)
Brong Ahafo	13 (1.0)	71 (5.3)	84 (6.3)
Northern	22 (1.6)	159 (11.9)	181 (13.5)
Upper East	29 (2.2)	157 (11.8)	186 (13.9)
Upper West	29 (2.2)	166 (12.4)	195 (14.6)
Total	183 (13.7)	1153 (86.3)	1336 (100)

364

365

366

367

368

369

370 Table 2: Logistic regression model

371

Parameter	Estimate (β)	Std. Error	z- value	Pr(> z)	95% Confidence Intervals		Odds ratio	MSE
Intercept	0.085417	1.379637	0.062	0.95063	-2.5697490	2.8503370	1.089171	1.9033700
Age	0.088379	0.097531	0.923	0.35590	-0.1034452	0.2726374	1.092402	0.00951215
Age sqd.	-0.00156	0.001575	-0.992	0.32107	-0.0045774	0.0016117	0.998441	0.00000024
Parity 2	0.342182	0.244936	1.397	0.16241	-0.1334970	0.8290040	1.408017	0.0599927
Parity 3*	0.607238	0.281534	2.157	0.03101	0.0611689	1.1677160	1.835355	0.0792600
Parity 4*	0.783020	0.333863	2.345	0.01901	0.1402631	1.4530570	2.188070	0.1114620
Parity 5*	1.179091	0.402977	2.926	0.00343	0.4119609	2.0000360	3.251417	0.1623880
Parity 6*	1.181578	0.498824	2.369	0.01785	0.2480639	2.2228760	3.259514	0.2488216
Parity 7	0.654110	0.493297	1.326	0.18484	-0.2915003	1.6513880	1.923429	0.2433382
Parity 8**	2.602640	1.086394	2.396	0.01659	0.8607378	5.5521170	13.49933	1.1802343
Parity 9	0.224840	0.703290	0.320	0.74920	-1.0966773	1.7057604	1.252122	0.4940094
Parity 10*	1.820419	1.157665	1.572	0.11584	-0.1206060	4.8441809	6.174445	1.3401682
ANC 2	-0.17949	1.105634	-0.162	0.87104	-2.0207868	2.7847656	0.835696	1.2224080
Locality 2	0.033159	0.202667	0.164	0.87004	-0.3639370	0.4314230	1.033715	0.0410733
Economic status 2	-0.02504	0.248776	-0.101	0.91984	-0.5103671	0.4674914	0.975271	0.0618880
Economic status 3	-0.22517	0.260080	-0.866	0.38661	-0.7333866	0.2883160	0.79838	0.0676405
Economic status 4	0.103000	0.285934	0.360	0.71868	-0.4529114	0.6702375	1.108491	0.08175702
Economic status 5	0.360045	0.326952	1.101	0.27080	-0.2758790	1.0079452	1.433394	0.1068960

372

373

374

375

376

377

378

379

380

381

382

383

384 Table 3: Bayesian Posterior analysis

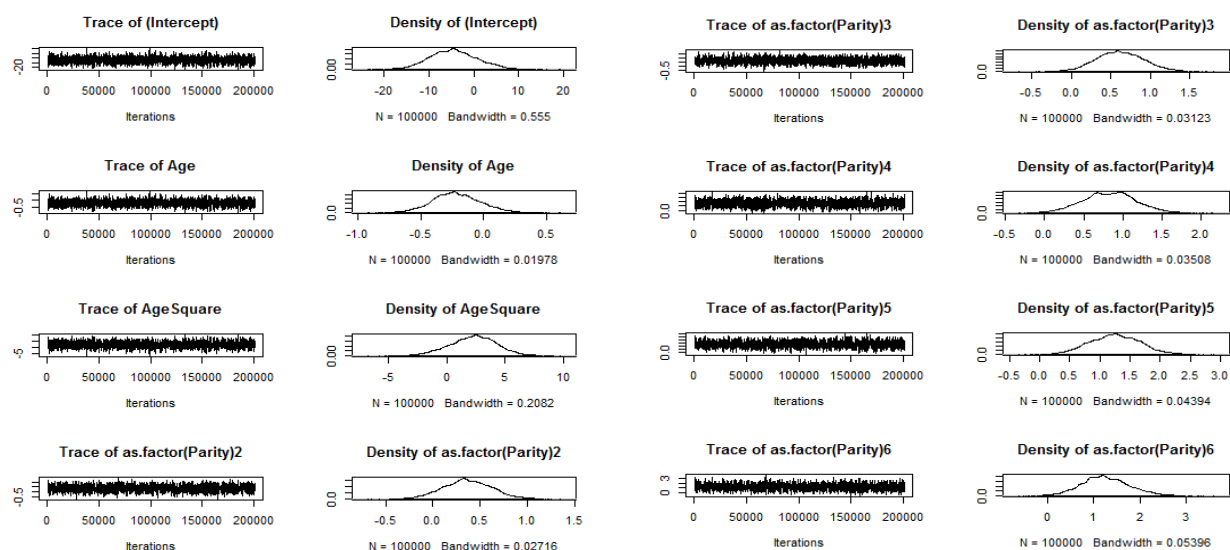
Parameter	Mean (β)	Std. dev.	Odds ratio	95% Bayesian Credible Interval		MSE	Std. Error
				Lower	Upper		
Intercept	-4.514712	5.3052	0.010947	-14.49495	6.1892	0.0211000	0.14530
Age	-0.216483	0.1887	0.805346	-0.57182	0.1685	0.0000267	0.00517
Age square*	2.256857	2.0140	9.553017	-1.80848	6.0158	0.0030400	0.05516
Parity 2	0.363909	0.2562	1.438943	-0.13795	0.8831	0.0000492	0.00701
Parity 3	0.619332	0.2946	1.857687	0.06318	1.2127	0.0000651	0.00806
Parity 4	0.827847	0.3352	2.288387	0.17143	1.4874	0.0000842	0.00918
Parity 5	1.249233	0.4146	3.487667	0.44757	2.0626	0.0001280	0.01130
Parity 6	1.259043	0.5216	3.522049	0.26459	2.3289	0.0002040	0.01420
Parity 7	0.711070	0.4961	2.036169	-0.23461	1.6805	0.0001840	0.01350
Parity 8**	3.168589	1.3237	23.77392	1.12369	6.2351	0.0013100	0.03620
Parity 9	0.347425	0.7295	1.415418	-1.03334	1.8242	0.0003990	0.01990
Parity 10	2.461445	1.3712	11.72174	0.14548	6.0874	0.0014100	0.03750
ANC 2	0.255195	1.3712	1.290713	-1.92678	3.4620	0.0014100	0.03750
Locality 2	0.024328	0.2045	1.024626	-0.37678	0.4290	0.0000313	0.00560
Economic status2	-0.007232	0.2531	0.992794	-0.50384	0.5040	0.0000480	0.00693
Economic status3	-0.230446	0.2618	0.794179	-0.75038	0.2933	0.0000514	0.00717
Economic status4	0.096833	0.2888	1.101676	-0.46341	0.6782	0.0000625	0.00791
Economic status5	0.400218	0.3309	1.492150	-0.25450	1.0546	0.0000821	0.00906

385 Table 4: Comparing results of Logistic Regression and Bayesian models

Frequentist analysis (Logistic Regression)							Bayesian Posterior analysis (Non-Informative Priors)					
Parameter	Mean (β)	S.E	S.D	Odds ratio	95% Confidence Intervals		Mean (β)	S.E	S.D	Odds ratio	95% Credible Intervals	
Intercept	0.0854	1.3796	50.37	1.0892	-2.57	2.85	-4.515	0.1453	5.31	0.0109	-14.49	6.19
Age	0.0884	0.0975	3.561	1.0924	-0.10	0.27	-0.216	0.0052	0.19	0.8053	-0.57	0.17
Age sqd.*	-0.002	0.0016	0.058	0.9984	-0.00	0.00	2.2569	0.0552	2.01	9.5530	-1.81	6.02
Parity 2	0.3422	0.2449	8.943	1.4080	-0.13	0.83	0.3639	0.0070	0.26	1.4389	-0.14	0.88
Parity 3	0.6072	0.2815	10.28	1.8354	0.06	1.17	0.6193	0.0081	0.29	1.8577	0.06	1.21
Parity 4*	0.7830	0.3339	12.19	2.1881	0.14	1.45	0.8278	0.0092	0.34	2.2884	0.17	1.49
Parity 5*	1.1791	0.4030	14.71	3.2514	0.41	2.00	1.2492	0.0113	0.41	3.4877	0.45	2.06
Parity 6*	1.1816	0.4988	18.21	3.2595	0.25	2.22	1.2590	0.0142	0.52	3.5220	0.26	2.33
Parity 7*	0.6541	0.3933	18.01	1.9234	-0.29	1.65	0.7111	0.0135	0.50	2.0362	-0.23	1.68
Parity 8**	2.6026	1.0864	39.66	13.499	0.86	5.55	3.1686	0.0362	1.32	23.774	1.12	6.24
Parity 9	0.2248	0.7032	25.68	1.2521	-0.10	1.71	0.3474	0.0199	0.73	1.4154	-1.03	1.82
Parity 10*	1.8204	1.1577	42.27	6.1744	-0.12	4.84	2.4614	0.0375	1.37	11.722	0.15	6.09
ANC 2	-0.179	1.1056	40.37	0.8357	-2.02	2.78	0.2552	0.0375	1.37	1.2907	-1.93	3.46
Locality 2	0.0332	0.2027	7.399	1.0337	-0.36	0.43	0.0243	0.0056	0.20	1.0246	-0.38	0.43
Economic status 2	-0.250	0.2488	9.083	0.9753	-0.51	0.47	-0.007	0.0069	0.25	0.9928	-0.50	0.50
Economic status 3	-0.225	0.2601	9.496	0.7984	-0.73	0.29	-0.230	0.0072	0.26	0.7942	-0.75	0.29
Economic status 4	0.1030	0.2859	10.44	1.1085	-0.45	1.67	0.0968	0.0079	0.29	1.1017	-0.46	0.68
Economic status 5*	0.3600	0.3270	11.94	1.4334	-0.28	1.01	0.4002	0.0091	0.33	1.4922	-0.25	1.05

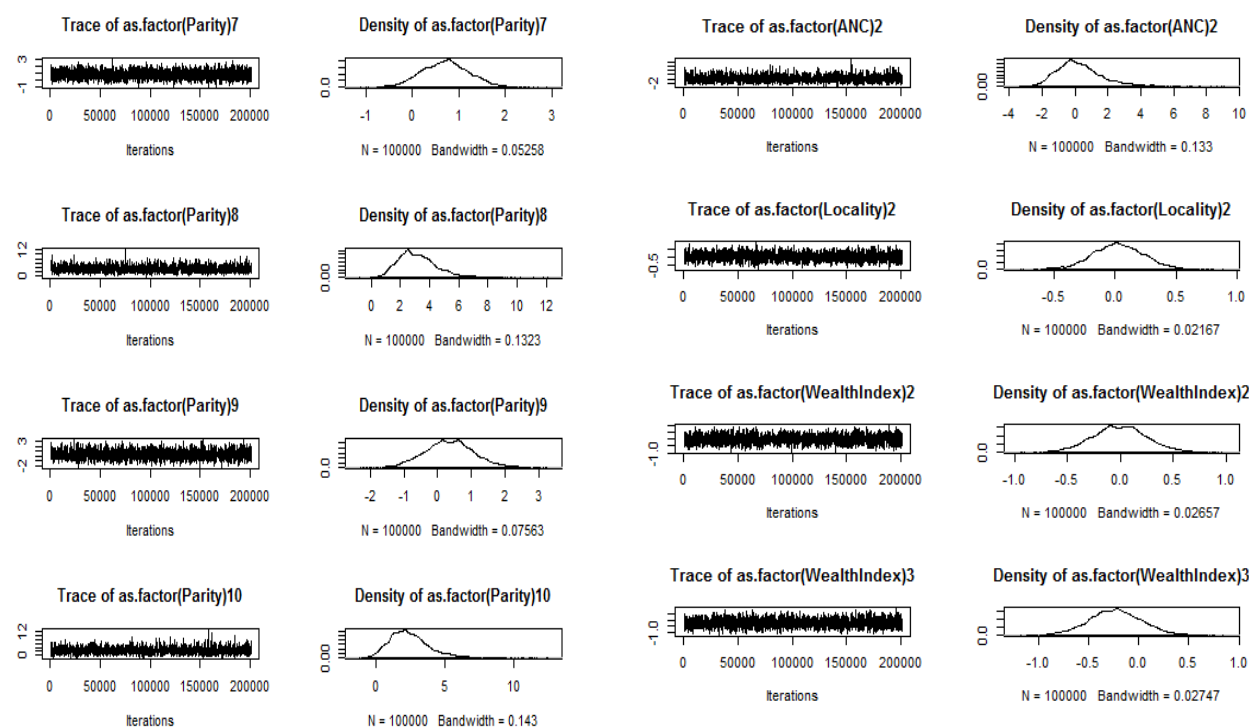
386 Figure 1: Density plots and Trace plots of the posteriors

387



389

390



392

393

References

1. Bategeka L., Leah M., Okurut A., Barungi M., Apolot J. M. (2009): The Determinants of Birth weight in Uganda. A Final Report Submitted to AERC, Nairobi, Kenya.
2. Bayarri, M.J. and Berger, J.O. (2004) The interplay of Bayesian and frequentist analysis. *Statistical science*, Vol. 19., No.1, pp. 58-80.
3. Deshmukh J.S. et al (1996) “Low birth weight and associated maternal factors in an urban area” (no.9)
4. Dunson D. (2001) Practical advantages of Bayesian analysis of epidemiologic data. *Am J Epidemiol*; 153(12): 1222-6.
5. El –Hakim IE, Uthman MA (1999): Squamous cells carcinoma and Keratoa-canthoma of lower lip associated with ‘Goza’ and ‘Shisha’ smoking. *Int J Dermatol*; 108-10
6. Etzioni R, Kadane J. (1995) Bayesian statistical methods in public health and medicine. *Public Health*; 16: 23-41
7. Ghana Statistical Service (2006): Multiple Indicator Cluster Survey; GSS
8. Ghana Statistical Service (2003): Ghana Demographic and Health Survey; GSS
9. Ghana Statistical Service (2008): Ghana Demographic and Health Survey; GSS
10. Ghana Statistical Service (2011): Multiple Indicator Cluster Survey; GSS
11. Gilks WR, Thomas A, Spiegelhalter DJ (1994). A language and program for complex Bayesian modelling. *Statistician*; 43: 169-78.
12. Gilks WR, Richardson S, Spiegelhalter DJ (1996) Eds. *Markov Chain Monte Carlo in Practice*. Chapman & Hall: London; pp. 1-19
13. Goodman S. (1999) Toward evidence-based medical statistics. 1. The P value fallacy. *Ann Intern Med*; 130: 995-1004
14. Greenland S. (2006) Bayesian perspectives for epidemiological research: I. Foundations and basic methods. *Int J Epidemiol*; 35: 765-75.
15. Marshall RJ. (1988) Bayesian analysis of case-control studies. *Stat Med*; 7: 1223-30.
16. Nurminen M, Mutanen P. (1989) Bayesian analysis of case-control studies. *Stat Med*; 8: 1023- 4.
17. Park K. (2007) *Text book of Preventive and Social Medicine*. 19th edition. Jabalpur Banarsidas Bhanot Publishers,. p. 426-428.
18. Pascale S, Mirna W, George K, Michele D (2014) Bayesian and Frequentist comparison for epidemiologist: A non mathematical application on logistic regression. 7, 17-26
19. Rosenzweig M.R, Schultz TP (1983) Estimating a Household Production Function: Heterogeneity, the Demand for Health Inputs, and Their Effects on Birth Weight. *Journal of Political Economy* 91:723–746
20. Sachdev H.P.S. (2001) Low birth weight in South Asia. *Int J Diab Dev Countries*; 21(1):13-33
21. Spiegelhalter DJ, Myles JP, Jones DR, Abrams KR. (2000) Bayesian methods in health technology assessment: a review. *Health Technol Assess*; 4(38): 1-130

- 434 22. Spiegelhalter DJ, Best NG, Carlin BI, van der Linde A (2002). Bayesian measures of
435 model complexity and fit. J R Statist Soc B; 64(4): 583-639.
- 436 23. UNICEF, 'Social Monitor 2003' (2003) UNICEF Innocenti Research Centre,
437 Florence, [<http://www.unicefcdc.org/publications>].
- 438 24. UNICEF/WHO (2004): Low birth weight; Country, Regional and Global estimates.
- 439 25. Zelen M, Parker RA. (1986) Case-control studies and Bayesian inference. Stat Med;
440 5: 261-9.