Bayesian Multilevel Model on Maternal Mortality in Ethiopia

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Abstract Maternal mortality is one of the socio-economic problems and widely considered a serious indicator of the quality of a health. Ethiopia is considered to be one of the top six sub-Saharan countries with severe maternal mortality. The objective of this study was to investigate the effects of the Demographic and Socio-economic determinant factors of maternal mortality in Ethiopia. Data from the 2016 Ethiopia Demographic and Health Survey indicated that the sample of women (15-49) was (n=10103). The Bayesian multilevel l was used to explore the major risk factors and regional variations in maternal mortality in Ethiopia. Markov chain Monte Carlo methods with non-informative priors have been applied. The Deviance Information Criterion model selection criteria were used to select the appropriate model. The analysis result, 145(1.43%) mothers were died due to pregnancy. Using model selection criteria Bayesian multilevel random coefficient was found to be appropriate. With this model, Age of mother, marital status, number of living children, wealth index and Education are found to be the significant determinants of maternal mortality in Ethiopia. The study indicated that there was within and between regional variations in maternal mortality. Inference is the fully Bayesian multilevel model based on recent Markov chain Monte Carlo techniques. Some of the socioeconomic, demographic and environmental determinants included in the study were found to be statistically significant. The result of the Bayesian multilevel model in this study has shown that educational attainment, wealth index, an age of mother, marital status and number of living children was a significant factor of maternal mortality.

Keywords: Demographic and Health Survey 2016, Ethiopia, Bayesian Multilevel, Random Intercept Logistic Regression Model, Maternal Mortality
1. Introduction

1.1. Background of the study
Maternal mortality is known as maternal death and major cause of death among women of reproductive age (World Health Organization, 2007). As explained in Shah and Say (2007), maternal mortality is the death of a woman while pregnant or within 42 days of termination of pregnancy. It caused by any related of the pregnancy but not from accidental or incidental causes. As World Health Organization, 2012 indicates that annually, 287,000 women die globally during a complication of pregnancy. At the country level, India at 19% (56,000) and Nigeria at 14% (40,000) account for a third of global maternal deaths. Ethiopia is one of the countries with the most serious problems by maternal mortality from the world. As World Health Organization, 2015 report Ethiopia is one of top six countries that contribute to about 50% of maternal mortality. Demographic and Health Survey data is hierarchical structure, in such case two sources of random variation was available. Thus the study was adopted Bayesian multilevel models, to examine the impact of contextual factors on maternal mortality and its variations among regions.

1.2. Statement of the problem
According to different previous study, the advantage of Bayesian approach over that of classical method has been certified. However, most of those studies were based on logistic which cannot be empowered to answer there were geographical variations or not (Ogunsakin, 2017, Weyesa, 2015). Besides, the other studies were conducted at hospital level with limited covariates; and based on the classical models that have relative drawback (Grzenda, 2015, Acquah H. D., 2013) Hence, this study was intended to entire the gap by considering the random effects under multilevel model of Bayesian paradigm.

Therefore the basic research questions are:
- Which variables have significant impacts on maternal mortality from the study variables?
- Is there variation of maternal mortality within and between Regional States of Ethiopia?
- From the study variables which predictors have variation across regions?

1.3. Objective of the study
General Objective: To identify and explain the effects of the Demographic and Socio-economic determinant factors on maternal mortality in Ethiopia.
Specific objective:
- To identify the factors associated with maternal mortality in Ethiopia.
- To examine the extent of the variation within and between regional variations of maternal mortality in Ethiopia.
- To determine from the study variables, the variation of predictors across regions.

1.4. The significance of the study
Despite the amount of work published as well as policies and initiatives being adopted in an effort to reduce maternal death; the problem are still not clear. Previous study was identify some variable for the cause and risk at specific level like hospital or district however these only present the level of maternal mortality at individual level not at national level. This research fills the statistical analysis by adopting an appropriate method which is hierarchical by its nature. In general; this research has a significant role for our country to identify the most serious determinants of maternal mortality. Bayesian multilevel logistic regression model that will help to take action on those identified determinants. Finally, this study would stimulate further research in the application of Bayesian multilevel model in the area of maternal health and mortality.

2. Methodology
2.1. Source of the data
The data used in this study is Ethiopian Demographic Health Survey, 2016 which was implemented by the (Central Statistical Agency) and (Ministry of Health). A total of sample of 10103 women between the ages of 15-49 years in Ethiopia was included in this study. All women age 15-49 and all men age 15-59 who were either permanent residents of the selected households or visitors who stayed in the household the night before the survey were eligible to be interviewed (Central Statistical Agency, 2016).

Variable of the study: In this study, the potential determinant factors expected to be correlated with pregnancy-related death are included as variables. This variable was

Response variable: The response variable in this study is the survival status of mothers at a reproductive age and this variable is dichotomous, coded as 1 if death due to pregnancy has occurred and 0 otherwise.
The predictor variables: Many explanatory variables were used as predictors of maternal mortality. The explanatory variables that included in this study were:

- Place of delivery
- Antenatal care
- Mother’s age at birth
- Place of residence
- Region
- Mothers education
- Marital status
- Wealth index
- Contraceptive
- Number of living children
- Source of drinking water

2.2. Method of Data Analysis

The statistical model that used for this data to analysis was the Bayesian multilevel logistic model. The data collection procedure is the hierarchical level or structures that means the levels are nested one another; Thus why the reason for selecting this model. MLwiN 2.02 version software was adopted for the analysis of this study.

2.2.1. Bayesian Multilevel Analysis of Empty Model (Null Model)

It is the probability distribution for group-dependent probabilities without taking further explanatory variables into account.

The null model is defined as:

\[ \logit (\pi_{ij}) = \beta_0 + U_{0j} \]  

The index i indicates individual for level one, j indicates region for level two,  \( U_{0j} \) is level two errors,  \( \beta_0 \) is the overall average of maternal mortality.

2.2.2. Bayesian Multilevel Analysis of Random Intercept Model

In the random intercept model the intercept is the only random effect meaning that the groups (region) differ with respect to the average value of the response variable.
The random intercept model expresses the logit of $\pi_{ij}$ as a sum of the linear function of explanatory variables and given as:

$$logit(\pi_{ij})= \log\frac{\pi_{ij}}{1-\pi_{ij}} = \beta_{0j} + \beta_1 X_{1ij} + \ldots + \beta_k X_{kij} = \beta_{0j} + \sum_{k=1}^{k} \beta_{hij} \quad \text{(2.3)}$$

Where the intercept term $\beta_{0j}$ is assumed to vary randomly and is given by the sum of an average intercept $\beta_0$ and group-dependent deviations $U_{0j}$ that is $\beta_{0j} = \beta_0 + U_{0j}$ as a result.

$$logit(\pi_{ij}) = \beta_0 + \sum_{k=1}^{k} \beta_{hij} x_{hij} + U_{0j} \quad \text{------------------------------------------ (2.4)}$$

Where $\beta_0 + \sum_{k=1}^{k} \beta_{hij} x_{hij}$ is the fixed part of the model and $U_{0j}$ is the random or stochastic part of the model.

### 2.2.3. Bayesian multilevel Analysis of Random Coefficients Model

The multilevel random effect coefficients logistic regression model is based on linear models for the log odds that include random effects for groups or other higher levels.

Consider a model with group-specific regression of logit of the success probability $\logit(\pi_{ij})$ on a single level -one explanatory variable $X$

$$logit(\pi_{ij}) = \log\frac{\pi_{ij}}{1-\pi_{ij}} = \beta_{0j} + \sum_{h=1}^{k} \beta_{hij} + U_{0j} + \sum_{h=1}^{k} U_{hj} x_{hij} \quad \text{------------------------------------------ (2.5)}$$

The term $\sum_{h=1}^{k} U_{hj} x_{hij}$ can be regarded as a random interaction between group and the explanatory variables. The random intercept variance, $\text{Var}(U_{0j}) = \sigma_0^2$, the random slope variance, $\text{Var}(U_{1j}) = \sigma_1^2$ and the covariance between the random effects, $\text{Cov}(U_{0j}; U_{1j}) = \sigma_{01}$ are called variance components (Snijders and Bosker, 1999).

### Likelihood Function

The key ingredients to a Bayesian analysis are the likelihood function, which reflects information about the parameters contained in the data, and the prior distribution, which quantifies what is known about the parameters before observing data

$$Y_{ij} / \pi_{ij} \propto Bernoulli(\pi_{ij})$$

$$\pi_{ij} = \log\frac{\pi_{ij}}{1-\pi_{ij}} = \beta_{0j} + \sum_{h=1}^{k} \beta_{hij} x_{hij} + U_{0j} + \sum_{h=1}^{k} U_{hj} x_{hij} \quad \text{------------------------------------------ (2.6)}$$
**Prior Distribution**
The prior distribution is a probability distribution that represents the prior information associated with the parameters of interest. It is a key aspect of a Bayesian analysis. Even if there is prior knowledge about what we are examining, in some cases we might prefer not to use this and let the data speak for themselves. In this case, we wish to express our prior ignorance into the Bayesian system. This leads to non-informative priors.

**The Posterior Distribution**
All Bayesian inferential conclusions are based on the posterior distribution of the model generated. Using the prior and likelihood function above the full conditional distribution of posterior parameter $\beta_0, \beta_1, \ldots, \beta_k$ is given by:

$$p(\beta_h | \Omega_u, U_{ij}, y_{ij}) \propto \prod_{ij} \pi_i^{y_{ij}} (1 - \pi_{ij})^{1-y_{ij}} \quad (2.7)$$

**2.3. Estimation Techniques**

**3.3.1. Markov Chain Monte Carlo (MCMC) Methods**
The use of Markov chain Monte Carlo (MCMC) methods to evaluate integral quantities has exploded over the last fifteen years. The initial definition required is that of a more primitive concept that underlies for the second MC which is called Markov chains. Metropolis–Hastings algorithm is a Markov chain Monte Carlo (MCMC) method for obtaining a sequence of random samples from a probability distribution.

**2.4. Model selection and comparison**
Model selection is to select the best model among several choices based on an evaluation of the performance of the models. A widely used statistic for comparing models in a Bayesian framework is the Deviance Information Criterion. In Bayesian, the lowest expected deviance has the highest posterior probability. Assessing goodness of fit involves investigating how close the values are predicted by the model with that of observed values (Bewick et al., 2005).

**2.5. Model Diagnostic**
The most common ways of checking goodness of fit are: diagnosis for convergence and mixing and posterior-predictive check. We have used the following in our study for convergence tests for the variables are: Time Series Plots, kernel density plot, Monte Carlo Standard Error (MCSE), the effective of sample size (ESS) and Partial Autocorrelation Function (PACF).
3. Results and Discussion

The response variable considered in this study was the maternal mortality (Death are related to pregnancy or otherwise). The highest percentage of maternal mortality was observed in Afar (2.93%) followed by Somalia (2.72%) while the lowest percentage of maternal death was recorded in Addis Ababa (0.46%) and followed by Dire Dawa (0.67%) in 2016. No antenatal visit and rural resident women were the highest frequency of maternal mortality. No educational attainment and poor wealth index women were also more affected women. Regarding with the age of mother's maternal mortality rate are 2.11%, 2.03%, 1.71%, 1.24%, 1.18%, 1.13%, 0.76% for mother's whose age are 40-44, 35-39, 30-34, 25-29, 15-45, 49 and 20-24 respectively.

Pearson chi-square test was applied to know predictors having a strong association with the response variable. The bivariate association between maternal mortality and predictors indicates that mother’s status related to pregnancy was strongly associated with place of delivery, age of mother, region, number of antenatal visit, place of residence, wealth index, marital status, contraception, educational attainment, source drinking water and number of child are found significant at 5% level of significance indicating that, association with maternal mortality.

Test of Heterogeneity: Hence Chi-square ($\chi^2$) test statistic was applied to assess the heterogeneity in the proportion of maternal mortality between regions in Ethiopia. The result obtained by cross tabulation in (Appendix Table 4.1) was $\chi^2 = 38.702$, df=10, p=0.000 $\alpha$= 0.05, hence we have enough evidence to reject the null hypothesis and conclude that there is heterogeneity of maternal mortality among regions of Ethiopia.

3.1. Bayesian Multilevel Logistic Regression Analysis of the Empty Model

The simplest important specification of the hierarchical linear model is a model in which only the intercept varies between level two units and no explanatory variables are entered in the model.

| Model                        | Coefficient | SD  | MCSE | 95%Cr.I          |
|------------------------------|-------------|-----|------|------------------|
| Fixed intercept ($\beta_0$)  | -5.257      | 0.359 | 0.0046 | (-6.048, -4.545) |
| Random intercept $\text{var}(u_{ij})=\sigma_{u0}^2$ | 3.966 | 1.811 | 0.0252 | (0.997, 8.012)   |

The overall mean of maternal mortality is estimated that $\beta_0 = -5.257$ found to be significant, suggest that evidence of regional effects on maternal mortality. The variance of the random factor is significant which indicates that there are regional differences in maternal mortality and
thus, Bayesian multilevel analysis can be considered as an appropriate approach for further analysis.

### 3.2. Bayesian Multilevel Logistic Regression Random Coefficient Model

It is possible to generalize the model so that the effect of level-1 covariates is different in each region. This can be done by adding random coefficients in front of some of the individual-level covariates of the model.

#### Table 1-3 Bayesian Estimates for Random coefficient model

| Fixed effect | Categories       | Estimates | SD   | MC error | 95% CI        |
|--------------|------------------|-----------|------|----------|---------------|
| Intercept    |                  | -4.955    | 0.880| 0.0979   | (-6.757, -3.407) |
| P.delivery   | Home (ref)       | -0.864    | 0.286| 0.001    | (-1.423, -0.306) |
|              | H. facilities    |           |      |          |               |
| N0 Ante.visit| No visit (ref)   | 1-2 visit | 0.352| 0.253    | (-0.148, 0.851) |
|              |                  | 3-4 visit | -0.210| 0.273    | (-0.759, 0.311) |
|              |                  | 5+ visit  | -0.46 | 0.344    | (-1.142, 0.192) |
| N0 children  | No child (ref)   | 1-2 child | 1.219| 0.717    | (-0.106, 2.654) |
|              |                  | 3-4 child | 1.925| 0.738    | (0.537, 3.426)  |
|              |                  | 5+ child  | 1.628| 0.749    | (0.174, 3.060)  |
| P residence  | Urban (ref)      | 0.666     | 0.447| 0.0037   | (-0.192, 1.598) |
|              | Rural            | 0.666     | 0.447| 0.0037   | (-0.192, 1.598) |
| E attainment | No educ (ref)    | Primary educ | -0.589| 0.267    | (-1.115, -0.076) |
|              |                  | Sec. and above | -1.069| 0.465    | (-2.040, -0.167) |
| Wealth index | Poor (ref)       | Middle    | -0.342| 0.270    | (-0.894, 0.189) |
|              |                  | Rich      | -1.296| 0.308    | (-1.927, -0.721) |
| Contraceptive| Not use (ref)    | Use       | -0.049| 0.274    | (-0.581, 0.469) |
| Random effect|                 | $\sigma_{\alpha 0}^2$ | 4.085| 1.222    | (1.659, 3.885)  |
|              |                  | $\sigma_{\alpha 20}^2$ | 31.193| 17.983   | (6.551, 70.06)  |
|              |                  | $\sigma_{\gamma 13}^2$ | 4.168 | 3.073    | (0.644, 12.69)  |

The odds of maternal death in health facilities was 58% (OR=0.42) times less likely than the odds of maternal death in a home. Regarding too number of antenatal visit the odds of maternal mortality for 1-2 number of antenatal visit was 1.42 more likely than that of no antenatal visits assuming all other factor constant, contradicting to this the odds of maternal death those who visit 3-4 and more than 5 number of antenatal visit was 0.81 and 0.64 less likely than the odds of
no antenatal visit by assuming other variable constant respectively. Another finding of this study indicates that the age of individual women is significantly associated with maternal mortality with 95% credible interval. Particularly, the odds of maternal mortality with age of mothers between 20-24 years was 1.17 times more likely to be dead than the odds of maternal mortality aged between 15-19 years and the odds of maternal death aged between 25-29 years were 1.98 times more likely to be dead than the odds of mothers age between 15-19 years. Educational attainment has a significant contribution to maternal mortality. The odds of pregnancy-related death of women for primary education was about 45% (OR=0.55) less likely than the odds of pregnancy-related death of women who have no education (illiterate) and the odds of maternal mortality for secondary and above education were about 66% (OR=0.34) less likely than the odds of maternal mortality for who has no education by assuming another factor constant.

The Bayesian multilevel logistic regression analysis result displayed in Table 4.4 below, also estimates the variance of random effect at the regional level, \( \text{var}(U_{0j}) \). Thus, the value of \( \text{var}(u_{0j})= 4.085 \) indicate there was significant variation (which means the 95% credible intervals is greater than zero). This confirmed the significance of the regional difference in maternal mortality in the regional state of Ethiopia. The researcher tried to identify to see the level of variation; that the intra-region correlation coefficient ICC is estimated as \( \rho = \frac{4.085}{4.085+3.29} =0.5538 \). This means that about 55.38% of the total variability in maternal mortality is due to differences across regions, with the remaining unexplained 44.62% attributable to individual differences.

This model contains a random slope for wealth index and the number of living children; which means that it allows the effect of the coefficient of this variable to vary from region to region. This model is more appropriate than the previous model for the variables being used since from wealth index category rich has fixed coefficient -1.296 (0.308), which suggests that this is the strong predictor and from wealth index category rich women were significantly less likely than poor women. It is necessary to see that the effect of wealth index on maternal mortality varies from region to region in Ethiopia which implies that there is a considerable variation in the effects of wealth index and the number of living children. The region wise intercept \( (U_{0j}) \) and slope \( (\text{wealth index}=U_{20j}) \) vary significantly, that is, there is a significant variation in the effects of these explanatory variables across the regions.
Another concept under this study the researcher revealed that the variance of the random slopes. The values of $\text{var}(u_{0j20}) = 31.193$ with credible interval of (95% CI: 6.551, 70.06) and $\sigma^2_{13} = 4.168$ with (95% CI: 0.644, 12.69) the interval was greater than zero. This indicates that the random slope of wealth index and the number of living children in the region is significant. This means that the wealth index and the number of living children factor for maternal mortality vary from region to region.

### 3.3. Model Comparison
Bayesian deviance information criterion showed that Bayesian multilevel random coefficient model is the most significant model and best fit the data.

Table 1-4 DIC values for model comparison

| Model                  | $\bar{D}$ | $D(\bar{\theta})$ | Pd | DIC  |
|------------------------|-----------|--------------------|----|------|
| Null model             | 1222.06   | 1061.04            | 161.02 | 1383.09 |
| Random intercept       | 1110.73   | 939.70             | 171.03 | 1281.76 |
| Random coefficient     | 1047.24   | 862.73             | 184.51 | 1231.75 |

### 3.4. Assessment of Model Convergence
The plots of all statistically significant covariates indicated that none of the coefficients have bimodal density and hence the simulated parameter values have converged. The ACF measures how correlated the values in the chain are with their close neighbors. The lag is the distance between the two chains to be compared. So, the plots displayed in Figure 4-1 below indicate low autocorrelation and efficient sampling as we have seen it. The Partial Autocorrelation Function (PACF) measures discrepancies from such a process and so should normally have values 0 after lag 1 which shows again convergence. The Monte Carlo Standard Error (MCSE) is an indication of how much error is in the estimate due to the fact that Markov chain Monte Carlo (MCMC) is used. As the number of iteration increased the Monte Carlo Standard Error (MCSE) was decreased as we have seen from the graph.
Discussion: These studies were attempted to identify some socio-economic and demographic determinants of maternal mortality in Ethiopia using 2016 EDHS data. Accordingly, the descriptive method and Bayesian Multilevel logistic regression were used in the analyses. The variables, having the significant association with maternal mortality (based on Chi-square test of association) place of delivery, Antenatal care, Mother's age at birth, Place of residence, Region, mothers education, Marital status, Wealth index, Contraceptive, number of living children, a source of drinking water. The Bayesian multilevel logistic regression empty model, the Bayesian multilevel logistic regression random intercept model, and Bayesian multilevel logistic regression random coefficient model were used in this study. From the result of the model adequacy Bayesian multilevel logistic random coefficient model is the best-fitted model (Spiegelhalter DJ, 2002).
The analysis based on Bayesian multilevel logistic regression provided estimates for variances of the random effects and interclass correlations. This means that the sources of variations are individuals and regions. The result of Bayesian multilevel logistic regression model comparison indicates that the random coefficient Bayesian multilevel logistic regression model best fits the model than the null model and random intercept model of the Bayesian multilevel logistic regression model. therefore the researcher suggests that Bayesian multilevel logistic regression for random coefficient were the best fit of the data and the interpretation was depend on random coefficients.

3.5. Conclusions and Recommendations

3.5.1. Conclusions
The study data was taken from the Ethiopian Demographic Health Survey conducted by the Central Statistical Agency (CSA) of Ethiopia in 2016. An inference is a fully Bayesian multilevel model based on recent Markov chain Monte Carlo techniques. The study was identified some socio-economic, demographic and environmental proximate variables as determinants of maternal mortality in the country and the gap from classical by checking the level of variation within and between region. From the methodological aspect, it was found that Bayesian multilevel random coefficient model is better compared to empty (null) model and random intercept model in fitting the data and in explaining the variations of pregnancy-related mortality across regional levels of Ethiopia. In addition from the empty model and random intercept model, the overall variance of the constant term was found to be statistically significant, implying the existence of a difference in pregnancy-related mortality in Ethiopia. The regional variations were high for the Bayesian multilevel empty model than the Bayesian multilevel for random intercept and lower for Bayesian multilevel for a random coefficient model to explaining the regional variation of 2016.

3.5.2. Recommendation
The findings of this study have some important policy implications and the identification of factors those are significantly associated with a maternal mortality. Depending on the above important findings, the researcher suggests the following recommendations for researchers and policymakers:

- Although the variation across the regions has been addressed with this study, the distribution for the prevalence of maternal mortality and the issue of identifying the hot-spot-area is not
covered here. Therefore, the researchers are recommended to extend this study with the application of spatial models.

- The data of this study was basically secondary which have the problem of missing data and the expected potential variables were also not availed. Thus, researchers should have to conduct the study on separate regions with the same models of this study.
- This study was limited to identifying the socio-demographic factors. However, there are other major causes of maternal mortality. Hence, we recommended researchers so that to study the significance of those causes by considering only maternal mortality using the Poisson model and its extension.

**Availability of Data and Materials**

The data set was taken from the Ethiopian Demographic and Health Survey (EDHS, 2016) website.

**Competing Interests**

The authors declare that not competing interest were available.

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**Author’s Contributions**

Shibiru Jabessa carried out the paper starting from data collection, analysis, and interpretation of data and drafted the manuscript. Dabala Jabessa participated in the data analysis, interpretation and critical review of the paper. Both authors’ read and approved the final draft of the manuscript.

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