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ON THE MODELING OF PER CAPITA HOUSEHOLD EXPENDITURE IN TANZANIA USING BAYESIAN TWO LEVELS HIERARCHICAL LOG-LOGISTIC APPROACH: THE CASE STUDY OF DODOMA REGION

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ABSTRACT

In Tanzania, the fight against poverty is a long-standing agenda, various efforts and initiatives were designed to eradicate poverty and increase economic growth among the citizen. However, there is evidence that real growth over the past decade has not been reflected in a rapid reduction in poverty rates. In this regard, the government needs an analysis of household welfare or poverty. The objective of this study is to get the best model and determine the factors that explain household expenditure. Household expenditure data has a hierarchical structure therefore modeling will be conducted using the two-level hierarchical linear model with the characteristic of households in the first level and district characteristics at the second level. The modeling is set on the basis of Log-logistic with three-parameter (LL3) and the estimation process is then accomplished by using a Bayesian approach with Markov chain Monte Carlo (MCMC) and Gibbs sampling algorithms. We found that three predictors in micro model among all are statistical insignificant. These factors are age of household head, level of education and gender of head. Furthermore, in macro model all estimated parameter of the district predictors was significant at 95% credible interval. It means that the four districts predictor effected on per capita household expenditure.

Keywords: *Bayesian Hierarchical Linear Model, Log-logistic Approach, MCMC, and Per Capital HE*

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Milimo Mashini ,
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CHAPTER 1
INTRODUCTION

1.1 Background of the Study

According to (World Bank, 2000), poverty defined as "pronounced deprivation of well-being." Well-Being comes from the capability to function in society (Haughton and Khandker, 2009). Thus, poverty arises when people lack vital capabilities, and so have inadequate income, education, poor health, insecurity, and low self-confidence. One of the economic indicators that widely used to measure a sense of well-being is income per capita. In this regard, the government needs analysis of per capita household income levels for the formulation, implementation, and evaluation of policies for the achievement of development goals.

However, Income, defined in principle as consumption plus the change in worth, it is generally used as a measure of welfare in developed countries (Haughton and Khandker, 2009), but it tends to be seriously understated in less-developed countries include Tanzania. To encounter the challenges of income, expenditure is mainly used because it is less understated and comes closer to measuring permanent income.

Besides, the size of expenditure is more reliable as an indicator of permanent household income; this is because spending does not fluctuate much in a short time. Welfare issues are influenced broadly by two categories namely the behavior paradigm and the policy paradigm. Behavior paradigm related to the efforts of each individual or household in achieving their level of welfare; Within each household, there some factors that play a crucial role in contributing behavior paradigm, such as the level of education and the number of household members, while the policy paradigm is related to economic conditions, politics, and government policy. Government policy is an external factor in the household that contributes to creating changes and improvements. Therefore, internal and external factors are influential factors of well-being in the household.

In Tanzania, the fight against poverty is a long-standing agenda. Various effort and initiatives were designed to eradicate poverty and increase economic growth include The Tanzania Development Vision 2025 designed in 1999, the National Poverty Eradication Strategy (NPES) designed in 1998 and Poverty Reduction Strategy Paper (PRSP) designed in 2000, all these initiatives set with the aim of eradicating poverty by 2025. Nevertheless, there is evidence that real growth over the past decade has not been reflected in a rapid reduction in poverty rates. The reported poverty rates (headcounts) were 28.2 percent in 2011/12 and 26.4 percent in 2017/2018 which is approximately 6.3 percent. This pessimistic assessment forms part of a broader set of concerns about the relationship between growth and individual well-being (Atkinson and Lugo, 2010).

In order to sharpen the formulation and implementation of government policies, Tanzania national bureau of statistics in collaboration with other stakeholders undertaken a series of research activities related to the analysis of household welfare levels. These surveys include Household and budget survey 2017/2018, the Tanzania HIV impact Survey 2016-17, and Economic survey 2018. The Household and Budget survey (HBS) is one of the surveys conducted using a two-stage cluster sample design. The first stage involved the selection of enumeration areas (primary sampling units – PSUs), the second stage of sampling involved systematic sampling of households from the updated PSUs list (NBS, 2018). Thus HBS data is a hierarchically structured data based on the sampling technique.

There are several studies conducted for modeling household welfare includes; (Grosh and Baker, 1995) using uni-level models with household characteristics as explanatory variables. (Iriawan et al., 2019) argue that the uni-level model is no longer appropriate for analysis of such hierarchical data due to its inefficient parameter estimates and negatively biased standard error. (Aprino and Aassve, 2007; and Haughton and Nguyen, 2010) modeled household expenditure data using hierarchical models for panel data in Vietnam using the estimation method with the Likelihood approach. (Iriawan et al., 2019; and Ismartini and Iriawan, 2013), using hierarchical linear with two models normal distribution and log-normal distribution respectively. The finding shows that both models can explain the variation. However, the diagnostic and cross-validation show that the log-normal model is more reliable to predict per capita household expenditure. Modeling of per capita expenditure in Maluku by (Irawati, 2015) shows that the variation (55.03%) in the micro model is significantly affected by household and district characteristics.

Generally, data in the social field, such as household expenditure data has a hierarchical data structure. Such data can be classified into different levels. This hierarchical data structure implies that units at the lower level are nested or clustered in units at a higher level.

The hierarchical model is a method developed for data analysis that involves two or more levels of relationship between variables and parameters. The model was first developed to analyze data with intricate diversity patterns. In many cases, complex diversity patterns refer to the hierarchical structure of the data.

According to (Hox, 2010), the use of the hierarchical model has several advantages. First, the hierarchical model can be used to analyze how many different levels are simultaneously in one statistical analysis; also, the models take account of the variance at each level of responses. (Woltman et al., 2012) argue that the hierarchical model can assess cross-level data relationships and accurately disentangle the effects of between- and within-group variance. It is also a preferred method for nested data because it requires fewer assumptions than other statistical methods (Raudenbush and Bryk, 2002). The results of this study prove that the hierarchical model is better than the classical model expressed by the mean square error (MSE) hierarchy model is smaller. While (Byaro et al., 2018) use the Bayesian method to determine factors influencing Public Health Expenditure growth in Tanzania using linear model, there is no information regarding the modeling of per capita household expenditure. Therefore, we need a statistical model as a measurement tool to predict household expenditure based on information collected from the Household budget survey.

1.2 Statement of the Problem

Although HBS 2017/18 report shows that the incidence of poverty level declined by 6.3% from 28.2% in the year 2011/2012 to 26.4% in 2017/2018, the actual cause of poverty and distribution is unknown.

Based on these discussions it is interestingly to find out how per capita household expenditure as the response variable can be explained by interactions between household and districts characteristics from each level of the hierarchical data structure

1.3 Research Objectives

The purposes of this study are:

1. To examine the distribution of per capita household in the Dodoma Region.
2. To estimate the best model which explain household expenditure
3. To determine factors that influence per capita expenditure.

1.4 Importance of the Study

The study will have the benefits as follow;

1. To develop insights and knowledge to practitioners, researchers and government institution
2. To evaluate project policy intervention by government geared to reduce poverty among the poor society in Tanzania

1.5 Limitations of the Study

1. The study was restricted to districts level rather than regional level
2. All districts are suppoting the independent variables

CHAPTER 2
LITERATURE REVIEW

2.1 Hierarchical Linear Model

Hierarchical levels of grouped data are a commonly occurring phenomenon (Woltman et al., 2012). Many data, including observational data collected in the biological sciences, social and economic aspects, have hierarchical, nested, or clustered structure (Goldstein, 1995). Previously it was difficult to analyze detail characteristics of these data but due to the development of this statistical method across many fields, it has come to be known by several names, including multilevel-, mixed level-, mixed linear-, mixed effects-, random effects-, and random coefficient (regression). For example, the organization of data in the education sector consists of several levels organized by student, classroom, school, and school district levels. In a social and economic related field, the data organization was presented as displayed in figure 2.1. This is hierarchical data structure with two-level, where the first level is household, and the second is Districts.

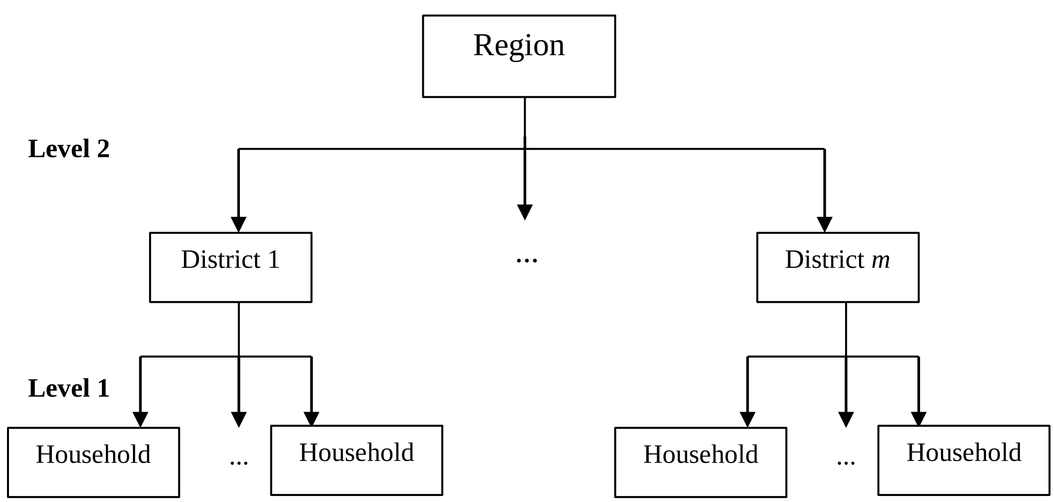

Figure 2.1 Two-Level Hierarchical Structure.

Analysis of hierarchical data is best performed using Hierarchical Linear modeling, the methods is a sophisticated form of ordinary least squares (OLS) regression that is used to analyses variance in the outcome variables when the predictor variables are at varying hierarchical levels (Woltman et al., 2012).

HLM accounts for the shared variance in hierarchically structured data: The technique accurately estimates lower level slopes (e.g., household level) and their implementation in estimating higher-level outcomes (e.g., district level). In the data structure of household expenditure with two levels, there will be m group of districts, where each group consists of n_j households. For example, $y_{1j}, y_{2j}, y_{3j}, \ldots, y_{nj}$ is the number of random variables for the jth group, and the number of observations for each group is n_j. Also $x_{1j}, x_{2j}, x_{3j}, \ldots, x_{pj}$, is the predictor variable at level one (micro predictor) for the jth group, and $G_1, G_2, G_3, \ldots, G_M$ are predictor variables at level two (macro predictor).

Model at Level 1

In two-level hierarchical models, separate level-1 models are developed characterised household for each level-2 unit (Districts). These models are also called within-unit models as they describe the effects in the context of a single group (Gill, 2003). They take the form of simple regressions developed for each individual. Model at this level can be written as follows.

$$y_{ij} = \beta_{oj} + \beta_{1j} x_{1ij} + \beta_{2j} x_{2ij} + \ldots + \beta_{pj} x_{pij} + e_{ij} \qquad (2.1)$$

where

$i = 1,2,\ldots,n_j$ and $j = 1,2,\ldots,m$.

y_{ij} = Dependent variable measured for ith level-1 unit nested within the jth level-2 unit

x_{ij} = predictors variable on the level-1

β_{pj} = Regression coefficient associated with x_{ij} the jth level-1 unit.

The equation (2.1) also can be written in vector form such as;

$$\mathbf{y}_{n\times 1} = \mathbf{X}_{n\times(p+1)}\boldsymbol{\beta}_{(p+1)\times 1} + \mathbf{e}_{n\times 1} \text{ and } \quad \mathbf{e_j} \sim N(0,\sigma^2 I_p) \quad \text{with}$$

$$y_j = \left[y_{1j}, y_{2j}, \ldots, y_{nj}\right]^T$$

$$\mathbf{X}_j = \begin{bmatrix} 1 & x_{11j} & x_{12j} & \cdots & x_{1pj} \\ 1 & x_{21j} & x_{22j} & \cdots & x_{2pj} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1j} & x_{n2j} & \cdots & x_{npj} \end{bmatrix}$$

$$\boldsymbol{\beta}_\mathbf{j} = \left[\beta_{0j}, \beta_{1j}, \ldots, \beta_{pj}\right]^T$$

$$\mathbf{e_j} = \left[e_{1j}, e_{2j}, \ldots, e_{pj}\right]^T$$

Model at Level 2

The Level-2 models also referred to as between-unit models as they describe the variability across multiple groups (Gill, 2003). In the level-2 models, the level-1 regression coefficients are used as outcome variables and are related to each of the level-2 predictors. The equation is as follow;

$$\beta_{rj} = \gamma_{0r} + \gamma_{1r}G_{1j} + \gamma_{2r}G_{2j} + \ldots + \gamma_{lr}G_{lj} + \mu_{rj}, r = 0,1,2,\ldots,p \quad (2.2)$$

or if expressed in vector form that is

$$\boldsymbol{\beta}_{m\times 1} = \mathbf{G}_{m\times(P+1)}\boldsymbol{\gamma}_{(P+1)\times 1} + \boldsymbol{\mu}_{m\times 1} \text{ and } \quad \boldsymbol{\mu}_r \sim N(0,\sigma^2 I_p)$$

$$\beta_r = \left[\beta_{r1,}\beta_{r2},\ldots,\beta_{rm}\right]^T$$

$$G = \begin{bmatrix} 1 & G_{11} & G_{21} & \cdots & G_{l1} \\ 1 & G_{12} & G_{22} & \cdots & G_{12} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & G_{1m} & G_{2m} & \cdots & G_{lm} \end{bmatrix}$$

$$\gamma_j = \left[\gamma_{0r,}\gamma_{1r},\ldots,\gamma_{1r}\right]^T$$

$$\mu_r = \left[\mu_{r1,}\mu_{r2},\ldots,\mu_{rm}\right]^T$$

The assumption for y_{ij} are as follows

1. $E\left(e_j\right)=E\left(\mu_p\right)=0$
2. $\operatorname{cov}\left(e_{ij},e_{ij}\right)=\operatorname{cov}\left(\mu_{pj},e_{ij}\right)=0, i\neq i^*, j\neq j^*, p\neq p^*$
3. $\operatorname{var}\left(e_j\right)=\delta_{ej}^2 I_{n_j}$
4. $\left(\mu_p\right)=\mathrm{T}_p$

$$T_p=\begin{bmatrix} \mu_{[\mu]p11} & \mu_{[\mu]p21} & \mu_{[\mu]p31} & \cdots & \mu_{[\mu]pm1} \\ \mu_{[\mu]p12} & \mu_{[\mu]p22} & \mu_{[\mu]p32} & \cdots & \mu_{[\mu]pm} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mu_{[\mu]p1m} & \mu_{[\mu]p1m} & x_{2nj} & \cdots & \mu_{[\mu]pmm} \end{bmatrix}$$

In order to allow for the classification of variables and coefficient in terms of the level of hierarchical they affect (Gill, 2003), a combined model (2.3) is created by substitution Equation (2.2) into equation (2.1)

$$y_{ij}=\beta_{oj}+\beta_{1j}x_{1ij}+\beta_{2j}x_{2ij}+\ldots+\beta_{pj}x_{pij}+e_{ij}$$

$$=\gamma_{00}+\gamma_{10}G_{1j}+\gamma_{20}G_{2j}+\ldots+\gamma_{l0}G_{lj}+\mu_{0j}+(\gamma_{01}+\gamma_{11}G_{1j}+\gamma_{21}G_{2j}+\ldots+\gamma_{l1}G_{lj}+\mu_{1j})X_{1ij}+$$
$$(\gamma_{02}+\gamma_{12}G_{1j}+\ldots+\gamma_{l2}G_{lj}+\mu_{1j})X_{2ij}+\ldots+(\gamma_{0k}+\gamma_{1k}G_{1j}+\ldots+\gamma_{lk}G_{lj}+\mu_{1j})X_{kij}+e_{ij}$$

$$=\gamma_{00}+\gamma_{10}X_{1ij}+\gamma_{20}X_{2ij}+\ldots+\gamma_{0k}X_{kij}+\gamma_{10}G_{1j}+\gamma_{20}G_{2j}+\ldots+\gamma_{l0}G_{lj}+\gamma_{11}G_{1j}X_{1ij}+\gamma_{21}G_{2j}X_{1ij}+\ldots$$
$$+\gamma_{l1}G_{lj}X_{1ij}+\gamma_{12}G_{1j}X_{2ij}+\gamma_{22}G_{2j}X_{2ij}+\ldots+\gamma_{l2}G_{lj}X_{2ij}+\ldots+\gamma_{1k}G_{1j}X_{kij}+\gamma_{2k}G_{2j}X_{kij}+\ldots\gamma_{lk}G_{lj}X_{kij}+\mu_{oj}$$
$$+\mu_{oj}X_{1ij}+\mu_{2j}X_{2ij}+\ldots+\mu_{kj}X_{kij}+e_{ij}$$

$=\gamma_{00}+\sum_{r=1}^{k}\gamma_{0r}X_{rij}+\sum_{q=1}^{l}\gamma_{qo}W_{qj}+\sum_{r=1}^{k}\sum_{q=1}^{l}\gamma_{qr}W_{qj}X_{rij}+\mu_{oj}+\sum_{r=1}^{k}\mu_{rj}X_{rij}+e_{ij}$ or if expressed in vector form that is

$$\mathrm{Y}_{n\times1}=\mathrm{X}_{n\times(p+1)}G_{m\times(p+1)}\gamma_{(p+1)\times1}+\mathrm{X}_{n\times(p+1)}u_{(p+1)+1}+\ell_{n\times1} \quad (2.3)$$

where

$X_j G_j \gamma$ = fixed (deterministic) in the hierarchical model.

$\mathbf{X_j u_j}$ = random (stochastic) in the hierarchical model.

$$\mathbf{E}\left(\mathbf{Y_j}\right) = \mathbf{X_j G_j \gamma},$$

$$\mathbf{var}\left(\mathbf{Y_j}\right) = \mathbf{X_j T X_j^T + \delta_j^2 I_{nj}}$$

The interpretation of the hierarchical model in equation (2.3) becomes quite complicated by the existence of the **G** variable. Based on the equation, the effect of variable **X** to **Y** depends on the variable **G**. Thus, the matrix **G** act as a moderator variable on the relationship between **Y** and **X** (Goldstein , 2010). The interpretation of the macro model regression coefficient and the regression coefficient of the macro model to **Y** depends on the positive and negative signals of both regression coefficients. If the coefficients $\boldsymbol{\gamma}$ are positive, then it can be said that **X** will have an interaction factor in the model because of the variable slope variation **X**. The moderator effect of **G** on the relationship between **X** and **Y** is expressed as cross-level interaction.

2.2 Bayesian Method

The Bayesian method adopted from the name of the inventor of the method, namely Thom Bayes 1702-17611 (Ismartini and Iriawan, 2013). Although the Bayesian method had existed since the 18^{th} century, it was until the early 20^{th} century with the development of information technology and the increasingly widespread use of computers so that data analysis that is difficult to do analytically can be obtained using a computer simulation solution.

Bayesian inference relies on Bayes theorem of probability and based on two general equations (Rencher and Schaalje, 2007). In these equations as presented below, y is a vector of n continuous observations, $h\left(y\right)$ is probability density functions and, $k\left(y,\theta\right)$ is the joint density of $y_1, y_2, y_3, \ldots, y_n$ and $\theta_1, \theta_2, \theta_3, \ldots, \theta_n$.

whereby θ is β and γ in level one and level two respectively.

$$g(\theta \mid y) = \frac{k(y,\theta)}{h(y)} \tag{2.4}$$

Using the definition of condition density, we can write an expression

$$g(\theta \mid y) = \frac{f(y \mid \theta)p(\theta)}{h(y)}$$

Which referred to as Bayes theorem and the marginal density obtained by integrating θ.

$$g(\theta \mid y) = \frac{f(y \mid \theta)p(\theta)}{\int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} f(y \mid \theta)p(\theta)d\theta} \tag{2.5}$$

In this expression, $p(\theta)$ it is known as the prior density of θ and $g(\theta \mid y)$ is called the posterior density of θ. The definite integral in the denominator is often replaced by a constant (c) because, after integration, it no longer involves the random vector θ. By rearranging this expression and integrating the joint density function $f(y \mid \theta)$ of the data as the likelihood function, $L(\theta \mid y)$ we obtain

$$g(\theta \mid y) \propto p(\theta)L(y \mid \theta) \tag{2.6}$$

2.2.1 Prior Distribution

The specification of the prior distribution is crucial in Bayesian since it influences the posterior distribution (Ntzoufras, 2009). It is highly recommended to specify prior mean and variance because prior mean provides a prior point of the estimate for the parameter of interest while variance explains uncertainty concerning the estimate. There are several types of prior distributions in Bayesian method, namely;

1. A class of prior pdfs for the family of distribution is said to define a conjugate family of distribution if the posterior pdf of the parameter is in the same family of the distributions as the prior (Hogg and Mckean, 2005).

2. A prior is said to be improper if it is not pdf, but the function of posterior distribution can be made proper.
3. Informative and non-informative prior is the prior related to the availability of the prior knowledge or information on the distribution of data. Jeffrey's (1961) proposed a general rule for the choice of non-informative prior.

In this research study the different prior distribution were used $\beta_{rj} \sim N\left(\mu_{[\beta]r}, \sigma^2_{[\beta]r}\right)$, with the PDF given as;

$$p\left(\beta_{rj}\right) = \frac{1}{\sigma^2_{[\beta]r}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\beta_{rj}-\mu_{[\beta]r}}{\sigma^2_{[\beta]r}}\right)^2} \tag{2.7}$$

$\lambda_j \sim N\left(\mu_{[\lambda]j}, \sigma^2_{[\lambda]j}\right)$ with PDF given

$$p\left(\lambda_j\right) = \frac{1}{\sigma^2_{[\lambda]j}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\beta_{rj}-\mu_{[\lambda]j}}{\sigma^2_{[\lambda]j}}\right)^2} \tag{2.8}$$

$\tau_{[\mathrm{y}]\mathrm{j}} \sim Gamma\left(a_{\left[\tau_{[\mathrm{y}]}\right]j}, \mathrm{b}_{\left[\eta_{[\mathrm{y}]}\right]j}\right)$, with PDF

$$p\left(\tau_{[\mathrm{y}]\mathrm{j}}\right) = \frac{1}{\Gamma\left(a_{\left[\tau_{[\mathrm{y}]}\right]j}\right)\mathrm{b}_{\left[\eta_{[\mathrm{y}]}\right]j}^{a_{\left[\eta_{[\mathrm{y}]}\right]j}}} x^{a_{\left[\eta_{[\mathrm{y}]}\right]j}-1} e^{-\frac{\tau_{[\mathrm{y}]\mathrm{j}}}{\mathrm{b}_{\left[\eta_{[\mathrm{y}]}\right]j}}} \tag{2.9}$$

$\gamma_{qr} \sim N\left(\mu_{\gamma_{qr}}, \sigma^2_{\gamma_{qr}}\right)$, and $\tau_{[\beta]r}$ is the conjugate prior distribution gamma for parameter $\sigma^2_{[\beta]r}$ from $p\left(\beta_{rj}\right)$ that follows $\tau_{[\beta]\mathrm{r}} \sim Gamma\left(a_{\left[\tau_{[\beta]r}\right]}, \mathrm{b}_{\left[\eta_{[\mathrm{y}]r}\right]}\right)$ with PDF

$$p\left(\tau_{[\beta]\mathrm{r}}\right) = \frac{1}{\Gamma\left(a_{\tau_{[\beta]\mathrm{r}}}\right)\mathrm{b}_{\eta_{[\beta]\mathrm{r}}}^{a_{\eta_{[\beta]\mathrm{r}}}}} x^{a_{\eta_{[\beta]\mathrm{r}}}-1} e^{-\frac{\tau_{[\beta]\mathrm{r}}}{\mathrm{b}_{\eta_{[\beta]\mathrm{r}}}}} \tag{2.10}$$

2.2.2 Posterior Distribution

The density function for θ is the probability function of θ with the observed sample y written as.

$$g(\theta \mid y) = \frac{f_L(y \mid \theta)\, p(\theta)}{h(y)} \tag{2.11}$$

the sample parameters can come from a discrete or continuous distribution. Posterior distributions contain all the θ parameter information or can be expressed in a $f\left(\theta/y\right)$ combination of prior information and observation data (likelihood function) so that the combined posterior distribution can be expressed in the equation.

$$P(y \mid \theta) = \frac{f_L(y \mid \theta)\, p(\theta)}{h(y)} \tag{2.12}$$

$h\left(y\right)$ is a constants density because it does not depend on parameters so it can be expressed in the following proportional form.

$$P(\theta \mid y) = f_L(y \mid \theta)\, p(\theta) \tag{2.13}$$

In the Bayesian Hierarchical LL3 modeling the posterior distribution obtained from the likelihood multiplication results and the prior distribution is as follows.

$$p(\beta,\gamma,\lambda,\tau_{[y]},\tau_{[\beta]} \mid y) = \frac{f_L(y \mid \beta,\lambda,\tau_{[y]})\, p_1(\beta \mid \gamma,\lambda,\tau_{[\beta]})\, p_2(\gamma,\lambda,\tau_{[y]},\tau_{[\beta]})}{h(y)} \tag{2.14}$$

where

$f_L(y \mid \beta,\lambda,\tau_{[y]})$ is a function of the likelihood of LL3 given by the the distribution;

$$f_L(y \mid \beta,\lambda,\tau_{[y]}) = \prod_{i=1}^{n} \frac{\exp\left(\dfrac{\ln(y-\lambda)-\beta}{\sigma}\right)}{(y-\lambda)\sigma\left[1+\exp\left(\dfrac{\ln(y-\lambda)-\beta}{\sigma}\right)\right]^2}$$

(2.15)

$p_1(\beta)$ is a conditional prior distribution function at the first level

$p_2(\gamma,\lambda,\tau_{[y]},\tau_{[\beta]})$ is a joint prior distribution function at the second level

$p_2(\gamma,\lambda,\tau_{[y]},\tau_{[\beta]}) = p(\gamma)\, p(\lambda)\, p(\tau_{[y]})\, p(\tau_{[\beta]})$ and

$$h(y)=\int\cdots\int f_L(y\mid\beta,\lambda,\tau_{[y]})\,p_1(\beta\mid\gamma,\tau_{[\beta]})\,p_2(\gamma,\lambda,\tau_{[y]},\tau_{[\beta]})\partial\beta_{01}\cdots\partial\beta_{km}\partial\gamma_{00}\cdots\partial\gamma_{ik}\partial\lambda_1$$
$$\cdots\partial\lambda_m\partial\tau_{[y]1}\cdots\partial\tau_{[y]m}\partial\tau_{[\beta]1}\cdots\partial\tau_{[\beta]k}$$

$h(y)$ is a constant density because it does not depend on parameters, consequently, equation 2.14 can be stated in proportional form as follows

$$p(\beta,\gamma,\lambda,\tau_{[y]},\tau_{[\beta]}\mid y)\propto f_L(y\mid\beta,\lambda,\tau_{[y]})\,p_1(\beta\mid\gamma,\lambda,\tau_{[\beta]})\,p_2(\gamma,\lambda,\tau_{[y]},\tau_{[\beta]})$$

(2.16)

because the prior distributions are independent then

$$p(\beta,\gamma,\lambda,\tau_{[y]},\tau_{[\beta]}\mid y)\propto f_L(y\mid\beta,\lambda,\tau_{[y]})\,p(\beta\mid\gamma,\tau_{[\beta]})\,p(\gamma),\,p(\lambda),\,p(\tau_{[y]}),\,p(\tau_{[\beta]})$$

(2.17)

Posterior distribution of the combined prior distribution given in equation 2.7, 2.8, 2.9 and 2.10 parameters and the likelihood parameter of the LL3 Bayes hierarchy model is is given bellow

$$p(\beta,\gamma,\lambda,\tau_{[y]},\tau_{[\beta]}\mid y)\propto\frac{\prod_{j=1}^{m}\tau_{[y]j}^{n_i/2}}{A}B\left(\prod_{r=0}^{k}\tau_{[\beta]r}^{1/2}\right)C\left(\prod_{r=0}^{k}\prod_{q=0}^{l}\tau_{[y]qr}^{1/2}\right)D\left(\prod_{j=1}^{m}\tau_{[\lambda]}^{1/2}\right)$$
$$E\prod_{j=1}^{m}\tau_{[y]j}^{a_{[\tau_{[y]]j}}-1}F_j\prod_{r=0}^{k}\tau_{[\beta]r}^{a_{[\tau[\beta]]r}-1}G_r$$

where

$$A=\prod_{j=1}^{m}\prod_{i=1}^{n_j}\left(y_{ij}-\lambda_j\right)\qquad(2.18)$$

$$B=\exp\left[-\frac{1}{2}\sum_{r=0}^{k}\tau_{[y]j}\left\{\sum_{i=1}^{n_j}\left(\ln\left(y_{ij}-\lambda_j\right)-X_{ij}^{T}\beta_j\right)^2\right\}\right]\qquad(2.19)$$

$$C=\exp\left[-\frac{1}{2}\sum_{r=0}^{k}\tau_{[\beta]r}\left\{\sum_{j=1}^{m}\left(\beta_{rj}-W_j^{T}\gamma_r\right)^2\right\}\right]\qquad(2.20)$$

$$D=\exp\left[-\frac{1}{2}\sum_{r=o}^{k}\sum_{q=0}^{l}\tau_{[\lambda]qr}\left(\lambda_{qr}-\mu_{[\lambda]qr}\right)^2\right]\qquad(2.21)$$

$$E = \exp\left[-\frac{1}{2}\sum_{j=1}^{m} \tau_{[\lambda]j} \left(\lambda_j - \mu_{[\lambda]j} \right)^2 \right] \tag{2.22}$$

$$F_j = \exp\left[-\frac{\tau_{[\lambda]j}}{b_{[\tau[y]]j}} \right] \tag{2.23}$$

$$G_r = \exp\left[-\frac{\tau_{[\lambda]j}}{b_{[\tau[\beta]]r}} \right] \text{and } W_j^T = \left[1, w_{1j}, w_{2j}, \ldots, w_{lj} \right] \tag{2.24}$$

the marginal posterior distribution for each parameter is obtained by integrating the equation. The estimation process is done through repeated sampling through the form of a posterior full conditional distribution. a posterior full conditional distribution combined all parameters to be estimated because the value is assumed to be fixed. The two-level Bayes hierarchy based on the LL3 distribution is as follows;

a) full conditional posterior distribution for β_{rj}

$$p(\lambda_j \mid y, \beta, \gamma, \lambda,_j, \tau_{[y]}, \tau_{[\beta]}) \propto BC$$

b) full conditional posterior distribution for λ_j

$$p(\lambda_j \mid y, \beta, \gamma, \lambda,_j, \tau_{[y]}, \tau_{[\beta]}) \propto \left(\frac{B}{A} \right) E$$

$\lambda_{\backslash j}$ is a vector λ without the element λ_j

c) full conditional posterior distribution for $\tau_{[y]j}$

$$p(\tau_{[y]} \mid y, \beta, \gamma, \lambda, \tau_{[y]|j}, \tau_{[\beta]}) \propto \frac{\prod_{j=1}^{m} \tau_{[y]j}^{n_i/2}}{A} B \prod_{j=1}^{m} \tau_{[y]j}^{a_{[\tau[y]]i-j}} F_j$$

$\tau_{[y]|j}$ is a vector $\tau_{[y]}$ without the element of $\tau_{[y]\backslash j}$

d) full conditional posterior distribution for $\gamma_{qr}, q = 0,1,\ldots,l$

$$p(\gamma_{qr} \mid y, \beta, \gamma_{|qr}, \lambda, \tau_{[y]}, \tau_{[\beta]}) \propto CD$$

$\gamma_{\backslash qr}$ is a vector γ without the element of γ_{qr}

e) full conditional posterior distribution for $\tau_{[\beta]r}$

$$p(\tau_{[\beta]r} \mid y, \beta, \gamma, \lambda,_{j}, \tau_{[y]}, \tau_{[\beta]\|r}) \propto B\left(\prod_{r=0}^{k} \tau_{[\beta]r}^{1/2}\right) C \prod_{r=0}^{k} \tau_{[\beta]r}^{a_{[\tau[\beta]]r}-1} G_r$$

$\tau_{[\beta]\backslash r}$ is a vector of $\tau_{[\beta]\backslash r}$ without element $\tau_{[\beta]\backslash r}$

2.2.3 Markov Chain Monte Carlo

In Bayesian, a significant limitation towards the implementation of Bayesian approaches is that obtaining the posterior distribution often requires the integration of high-dimensional functions (Geyer, 2004); Thus, computationally is very difficult, but with the use of several approaches short of direct integration have become comfortable.

Markov Chain Monte Carlo (MCMC) approaches are so-named because one uses the previous sample values to generate the next sample value randomly; the methods attempt to simulate direct draws from some complex distribution of interest.

A Markov chain is a stochastic process $\left\{\theta^{(1)}, \theta^{(2)}, \ldots, \theta^{(T)}\right\}$ such that

$$f(\theta^{(t+1)} \mid \theta^{(t)} \cdots, \theta^{(1)} = f(\theta^{(t+1)} \mid \theta^{(t)})$$

That is, the distribution of θ at sequence $t+1$ given all the other θ values (for times t, $t-1$…..,1) depends only on the value $\theta^{(t)}$ of the previous sequence t. Moreover, $f(\theta^{(t+1)} \mid \theta^{(t)})$ it is independent of time t (Ntzoufras, 2009). The algorithms of obtaining a sample from posterior using MCMC are as follows;

1. Select an initial value $\theta^{(0)}$
2. Generate T values until the equilibrium distribution.
3. Monitor the converge of the algorithm using convergence diagnostics. If convergence.
4. Cut off the first B observations.
5. Consider $\left\{\theta^{(B+1)}, \theta^{(B+2)}, \ldots, \theta^{(T)}\right\}$ the sample for the posterior analysis.

6. Plot the posterior distribution (usually focus is on the univariate marginal distributions).
7. Finally, obtain summaries of the posterior distribution (mean, median, standard deviation, quantiles, correlations).

2.2.4 Gibbs Sampling

The two most popular MCMC methods are The Metropolis-Hastings algorithm and the Gibbs sampling (Ntzoufras, 2009). The roots of the method, however, can be traced back to at least (Metropolis et al., 1953), with further development by (Hastings, 1970; and Casella and George, 1992)

This technique involves generating random variables from a distribution indirectly, without having to calculate the density. Although straightforward to describe, the mechanism that drives this scheme may seem mysterious.

Given the joint density $f(x, y_1, y_2, y_3, \ldots, y_n)$ and our interest is in obtaining characteristics of the marginal density $f(x)$ such as the mean or variance. In these cases, the Gibbs sampler provides a method for obtaining $f(x)$ by effectively to generate a sample $(x_1, x_2, x_3, \ldots, x_n)$ without requiring $f(x)$.

This is one of the advantages of Gibbs Sampling because the random variable is generated using the unidimensional distribution concept which is structured as a full conditional form.

If θ is a vector of a set of parameters to be estimated, then a full conditional posterior distribution generated for each parameter element of θ. A full conditional posterior distribution for θ_j is formed from the combined posterior distribution of all parameters in vector θ. The algorithm summarized by the following steps (Ntzoufras, 2009). In the case of logistic three-parameter, it means $\theta = (\alpha, \beta, \gamma)$, so the posterior shape jointed is $\pi(\alpha, \beta, \gamma \mid y)$. Gibbs sampler will help estimate the parameter (α, β, γ) and iteratively by following the sampling scheme explained above for log-logistic distribution.

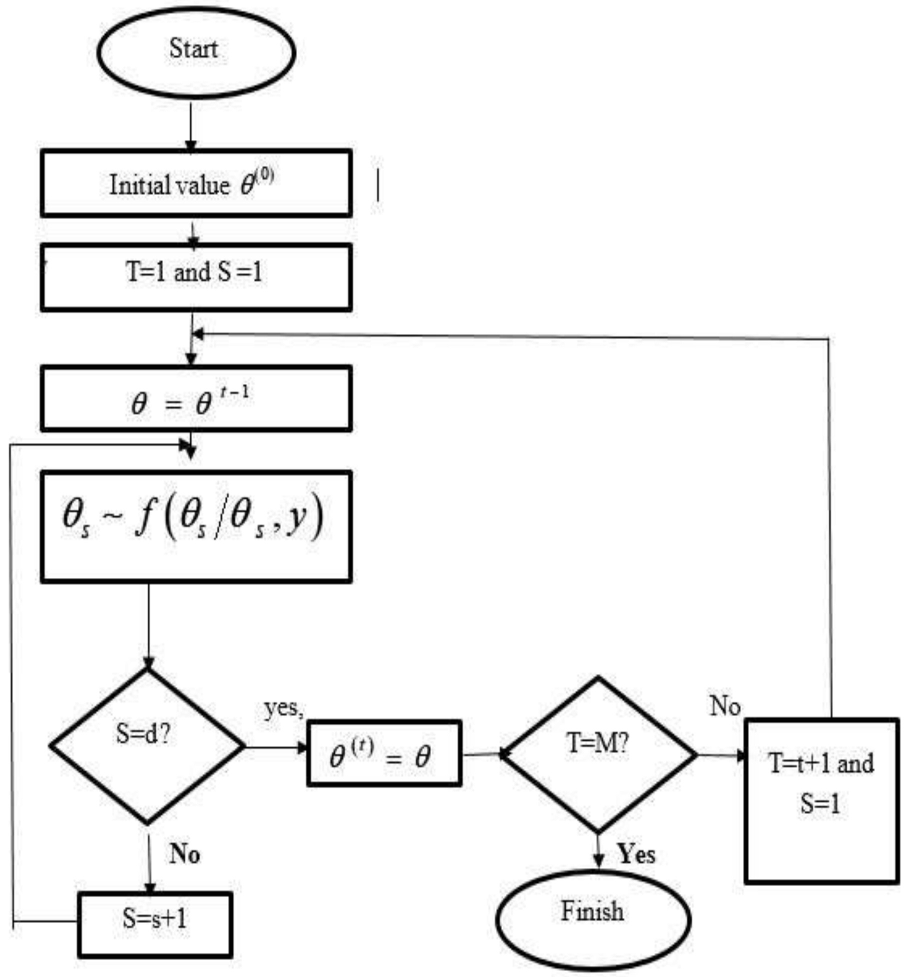

Figure 2.2 Diagram Show Gibbs Sampling

2.3 Win BUGS Program

Win BUGS is a programming language based software that is used to generate a random sample from the posterior distribution of the parameters of a Bayesian model (Ntzoufras, 2009). The acronym of BUGS stands for the initials of the phrase" Bayesian Inference Using Gibbs Sampling."

The original aim of the Win BUGS project was to develop software for producing the

MCMC sample from the posterior distribution of the parameter of the desired model. A model can be specified in the Win BUGS using a relatively simple code that is similar to the popular S language used in R and Splus statistical programs. Users who are not familiar with programming can specify the model structure by drawing its directed graphical structure in the DOODLE interface of Win BUGS.

The summary of obtaining the posterior sample of the model in Win BUGS can be summarized as follow;

1. Prepare the ODC file-write the model code, specify data, and initial values.
2. Compile and initialize the values
3. Run the model to generate a random sample
4. Perform output analysis using Win BUGS
5. Apply convergence test using BOA/KODA or other software

2.4 Kolmogorov Smirnov Test

Kolmogorov-Smirnov test is a non-parametric test for equality of continuous probability distributions that can be used to compare a sample with reference probability distribution or to compare two samples (Ajibade and Ukponmwan, 2017). It is an empirical distribution function (EDF) test in which the theoretical cumulative distribution function of the test distribution compared with the EDF of the data (Öztuna and Elhan, 2006).

The hypothesis test is defined as;

H_0: The data value of Y distributed according to the distribution F(x)

H_1: Data value of Y distributed according to the distribution F(x)

The test statistic used is as follows: $D_n = \sup \left| F_n(x) - \hat{F}(x) \right|$

H_0 Is rejected if $D_n \geq d_n$ or p-value < alpha,

where

d_n is the value taken from the Kolmogorov Smirnov table and

D_n is the most significant difference between $F_n\left(x\right)$ and $\hat{F}(x)$.

In this study, the distribution of the data was investigated using Easy-Fit software, and the Kolmogorov-Smirnov test was suitable.

2.5 Distribution Log-Logistic Three-Parameter

Household expenditure from Dodoma was identified and tested by using Easy-Fit Software, the logistic three-parameter is the suitable fit for per capita expenditure data. A random variable is said to follow log-logistic if the logarithm of the variable has logistic distribution. Log-logistic is a continuous positive random variable distribution with the right-skewed pattern. (Snijders and Bosker, 2002). The distribution commonly used as a growth curve and to model binary response, also very often used in biostatistics and economic fields. (Johnson et al.,1995, quoted by (Ismartini and Iriawan, 2013).

If **z** has a logistic distribution $\left(\mu,\sigma\right)$ with pdf;

$$f(z \mid \mu,\sigma) = \frac{\exp\left(\dfrac{\ln(Z)-\mu}{\sigma}\right)}{y\sigma\left[1+\exp\left(\dfrac{\ln(Z)-\mu}{\sigma}\right)\right]^2}, \qquad y>0, \mu>0, \sigma>0 \qquad (2.21)$$

Then $Y=\exp\left(Z\right)$ has LLD $\left(\mu,\sigma\right)$ with pdf (Balakrishnan & Norman, 1995)

$$f(y \mid \mu,\sigma) = \frac{\exp\left(\dfrac{\ln(y)-\mu}{\sigma}\right)}{y\sigma\left[1+\exp\left(\dfrac{\ln(y)-\mu}{\sigma}\right)\right]^2}, \qquad y>0, \mu>0, \sigma>0 \qquad (2.22)$$

With μ location parameter and δ is a scale parameter.

If the log-logistic distribution (LLD) is expanded by adding on threshold γ parameter so that the probability value of y less than λ is equal to zero, then ***y*** will have a three-parameter log-logistic distribution with pdf

$$f(y \mid \mu,\sigma,\lambda)=\frac{\exp\left(\frac{\ln(y-\lambda)-\mu}{\sigma}\right)}{(y-\lambda)\sigma\left[1+\exp\left(\frac{\ln(y-\lambda)-\mu}{\sigma}\right)\right]^2},\quad y>0,\mu>0,\sigma>0 \qquad (2.23)$$

The mean and variance from LLD (2.23) given as

$$E(Y)=\exp(\mu)\Gamma(1+\sigma)\Gamma(1-\sigma)+\lambda$$

$$\operatorname{var}(Y)=\exp(2\mu)\left[\Gamma(1+2\sigma)\Gamma(1-2\sigma)-\Gamma^2(1+\sigma)\Gamma^2(1-\sigma)\right].$$

2.6 Credible Interval

The fundamental difference in statistical inferencing with the classical approach and the Bayesian approach is in the formation of a confidence interval. In the classical approach, the confidence interval is known as a confidence interval that is formed based on the distribution of parameter estimates. Whereas in the Bayesian approach the confidence interval is formed by the highest posterior density (HPD) approach known as the Bayesian Confidence Interval or credible interval (Koop and Tobias, 2007) and (King and Morgan, 2010). Credible intervals can be used to create confidence intervals of asymmetrical data patterns (Box and Tiao, 1973: and Gelman et al., 2004). If ***y*** is a random variable with pdf $f(y \mid \theta)$ and θ is parameters to be estimated, then 100 (1-∝)% credible intervals for θ is:

$$p(\theta \in [a,b] \mid y)=\int_a^b f(\theta \mid y)d\theta = 1-\alpha \qquad 0<\alpha\le 1 \qquad (2.24)$$

Equation (2.18) shows that $\boldsymbol{\theta}$ is a random variable with a fixed interval. The credible interval is not unique so there will be several possible interval intervals [a, b] containing 100(1-α)% posterior distribution (King et al., 2010).

2.7 Parameter Significance Test

The parameter significance test is used to determine which parameter is significant so that they can be used in the model; credible interval test parameter significance the test is used in the Bayesian method. These tests define the posterior parameters lie within the interval. For each parameter, hypothesis testing is as follows;

$$H_0 : \phi = 0 \qquad H_1 : \phi \neq 0$$

Reject H_0 is based on the 95% credible interval from the posterior distribution such that if the credible interval loads zero then H_0 is accepted (Gelman et al., 2008)

2.8 Model Selection Criteria

The model used in this study is more than one, therefore a measure that can easily identify which model is better than the others which are Deviance information criteria (DIC), Means square error (MSE), Standard Error (SE) and coefficient of determination

2.8.1 Deviance Information Criteria

The deviance information criteria were introduced by Spiegel halter as the measure of model comparison and adequacy (Ntzoufras, 2009). A low value of DIC indicates a better-fitted model and the expression gives it

$$DIC = D\left(\overline{\theta}\right) + 2P_D \tag{2.25}$$

where

$D(\overline{\theta})$ is the deviance measure of a posterior mean parameter with the following formula;

$D\left(\overline{\theta}\right) = -2\log f\left(y \mid \overline{\theta}\right)$. Therefore, the equation (2.25) written as

$DIC = -2\log f\left(y \mid \overline{\theta}\right) + 2P_D$

While P_D can be interpreted as the number of useful parameters in the model, written with the following equation $P_D = \overline{D(\boldsymbol{\theta})} - D\left(\overline{\boldsymbol{\theta}}\right)$.

The more feasible determination of the model carried out by comparing the DIC value of the possible model. A model with a smaller DIC value indicates a better model for explaining variation in the response variable.

2.8.2 Mean Square Error

In statistical modeling, MSE is the one way that can be used to evaluate the model based on the difference between the estimated value and the actual value. A good model can be indicated from a small MSE value which is the calculation is carried out by the following expression (Balakrishnan and Norman, 1995).

$$MSE = E\left(\sum_{i=1}^{n} \left(\widehat{\theta}_i - \theta_i \right)^2 \right)$$

Furthermore, the standard error(SE) is the root of MSE

$$SE = \sqrt{E\left(\sum_{i=1}^{n} \left(\widehat{\theta}_i - \theta_i \right)^2 \right)}$$

2.8.3 Coefficient of Determination

The coefficient of determination or the squared multiple correlations is the measure of model fit and explains how well predictors can explain the variation in the response variable (Rencher & Schaalje, 2007). The coefficient of multiple correlations is denoted by R^2 and is given by the following expression

$$R^2 = 1 - \frac{SSE}{SST},$$

where $SSE = \sum_{i=1}^{n} \left(Y_i - \widehat{Y}_i \right)^2$ and $SST = \sum_{i=1}^{n} \left(Y_i - \overline{Y}_i \right)^2$

2.9 Per Capita Household Expenditure

Per capita, household expenditures are expenditures for household consumption, such as all goods and services that obtained used or paid for by the household, but it is not for business purposes and not for investment. Some expenses are not including household consumption expenses, among others:

1. Expenditures for businesses
2. Expenditures for investment, purchase of land, buildings, certificates of savings, and other items for investment.
3. Expenditures for parties, fines, and gambling
4. Giving to other parties. donations and lost
5. Payment of insurance premiums and pension fund contributions.

Average monthly per capita expenditure is the cost incurred for the consumption of all household members for a month divided by the number of household members (NBS, 2018). Household consumption is distinguished from food and non-food consumption without regard to the origin of the goods and is limited to expenses for household needs only. Mathematically, the formula for average expenditure per capita of households is:

$$y_{ij} = \frac{E}{N_{HS}}$$

where

y_{ij} = Per capita expenditure in a household for a month

E = Total household expenditure in a month

N_{HS} = Number of household members.

Consumption or expenditure is better in estimating living standards than income because income usually varies significantly compared to expenditure or consumption (Rusastra and Napitupulu, 2007). Besides, income fluctuates from year to year, and generally fluctuates in one's life, while consumption remains relatively stable. Household expenditure patterns are one indicator that can be used to measure the economic welfare of the population.

2.10 Factors Affecting Household Per Capita Expenditure

Household expenditure or household per capita expenditure has widely implemented as a response variable in poverty and welfare analysis. Meanwhile, the predictor variable uses factors that determine differences in household expenditure (Haughton and Khandker, 2009) explain that these factors include regional, community, household, and individual characteristics detailed in Table 2.1.

Table 2.1 Factors Affecting Differences in Expenditures among Households

Characteristics	Explanation
Regional level	– Quality of governance – Remoteness – Property right and enforcement
Community Level	– Availability of infrastructures like road and water – Availability of services like school and hospital.
Household Level	– Household size – Dependence ratio – Gender of the head of household – Asset ownership – Ration working member of the household
Individual Level	– Age – Education – Working status – Health status

Demographic Characteristic

Demographic characteristic includes the structure, size of household, and dependency ratio.

a) Household size and characteristics of household members often differed between one household and another.

b) Dependence ration defined as the ratio of the number of non-labour members of the households (both young and adult) against household members who are the labour force.

Economic characteristics

Isolation/remoteness includes a lack of infrastructure and demanding access to public services such as markets. Primary resources include availability and size of land Weather such as hurricanes, droughts, and environmental conditions such as frequency of national and regional government earthquakes

employment, open unemployment rates. Unemployment rate half-open, and type of work. The economic characteristic includes employment and property ownership

a) Household employment, several indicators determine household employment status. Economist focus on whether an individual is employed, how many hours they work, whether they hold multiple jobs and how often they change employment

b) Ownership of property in the form of ownership of goods with high value (land, livestock, agricultural equipment, buildings, and other durable fodder) and ownership of financial assets (assets that are easy to cash, savings, and other financial assets). This indicator reflects the ownership of household wealth inventory that influences household income and expenditure flows.

Social Characteristics

Social characteristics related to poverty include health. Education and residence.

a) Health in the household, including nutritional, disease, availability of health services, use of health services by households.

b) Education, this indicator covers the level of education of household members, the availability of educational services, and the use of education services by households.

c) Shelter. Three indicators are used to evaluate the condition of the residence, housing, services, and the environment. Housing indicators include size and type of building, the status of residence (rent or own), and type of household equipment. Service indicators include availability and use of drinking water, communication services, electricity, fuel. and other energy sources. Whereas environmental indicators include the level of sanitation, the level of isolation (availability of road access, the length of travel time, and the availability of transportation to the workplace) and the level of security.

(Chaudhry, 2009) uses the variable head of marital status (household head), household sex, household head, household head education level, household business field, household head work status, and head household activities. These variables are used to identify household welfare. The results of the study indicate, in general, the primary employment of households in the agricultural sector, the low education of the head of the household, and the number of household members is the main factor that causes the low welfare of a household.

CHAPTER 3
METHODOLOGY

3.1 Data Source

The data used in this study obtained from NBS where both micro and macro data are from a Household budget survey of 2017/2018 with per capita household expenditure, household characteristics as well as district (macro) characteristics.

In research with a two-level hierarchy method, the observation divided into two levels. The first level observation unit was sample household from Dodoma region, with sample distributed by the district characteristic data.as in Table 3.1, while in the second level, the observation unit is districts in the Dodoma region.

Table 3.1 Total Household Sample in Dodoma

No	**Districts**	**Total sample**
1.	Kondoa	36
2.	Mpwapwa	48
3.	Kongwa	60
4.	Chamwino	48
5.	Dodoma	70
6.	Bahi	35
7.	Chemba	36
Dodoma Region Sample Total		233

3.1.1 Variable Description

Variable used in this study include the response variable (Y), predictor micro variable (X), and predictor macro variable (G). The micro variable present relates to the characteristic of the household, while the macro variable represents district characteristics.

Table 3.2 Descriptions of Variables in Level 1 and 2

Variable	Description	Level	Data scale
Y	Average expenditure per capita of households per month		Continuous
X_1	Age of Household Head		Continuous
X_2	Head household working	0 Unemployed , 1 Employed	Category
X_3	Household farming	0 No, 1 Yes	Category
X_4	Highest level of education of head household (HH)	0 No education 1 Primary education, 2 Secondary and above	Category
X_5	Number of a household member		Discrete
X_6	Source of drinking water	0 Piped water to yard/plot, 1 Paped water into dwelling, 2 Public tap, 3 Bore hole, 4 Spring, 5 Tunker truck, 6 Surface water	Category
X_7	The main source of cooking	0 Electricity, 1 Solar, 2 Gas, 3 Charcool, 4 Wood	Category
X_8	Source of lighting	0 Firewood, 1 Electricity, 2 Solar, 3 Kerosine, 4 Recharchable Lamb	Category Category
X_9	Gender of Head	0 Female, 1 Male	Category
X_{10}	Mobile phone	0 No, 1 Yes	Category
X_{11}	Tellevision	0 No, 1 Yes	Category
X_{12}	Refregirator	0 No, 1 Yes	Category
X_{13}	Ox-plough	0 No, 1 Yes	Category
G_1	Population density		Continuous
G_2	The ratio of health facilities per 100,000 population		Continuous
G_3	The ratio of education facilities per 1000 school-age population		Continuous
G_4	The ratio of healthy person per 100,000 population		Continuous

Definition of the Variables

1) The average expenditure per capita of households per month (Y) is the total monthly household expenditure divided by the number of household members. Expenditures are defined as expenses for household needs/household members only, excluding consumption/expenses for household business needs, or those given to other parties/people.
2) Age of Head of household (HH) is an aged calendar from the day of birth to the date of the enumeration process.
3) Household dependency ratio (X_2). i.e., comparison between the number of children aged 0-14 years plus the number of adults 65 years and above (age group not the labour force) compared to the population age 15-64 years (labour force).

4) Head household working works (X_3). The household head considered to be working if carrying out activities/work to obtain or help to obtain an income of at least one hour continuously in the past week during the enumeration.
5) Farming households (X_4), Is households with a minimum of one household member who works on agriculture.
6) Highest level of education of head household (X_5). That is the highest level of education completed by the household head.
7) The number of household members (X) is the total of people who usually live and eat in these households, both core household members and outside core members.
8) Source of drinking water(X_7) that is the primary source of drinking water used by household include piped water, well and spring
9) The primary source of cooking (X_8) Types of fuel used by households for daily cooking.
10) Source of lighting (X_9) That is the primary source of lighting used by the household, such as electricity, solar panel, and fuel.
11) Population density (G_1) is the number of the population divided by the total area in the districts.
12) The ratio of health facilities per 100,000 population (G_2) Number of public hospitals, maternity hospitals, and polyclinics, divided by population times multiplied by 100,000
13) The ratio of education facilities per 100,000 school-age population (G3).
14) The ratio of healthy persons per 100,000 population (G4). The number of general practitioners, dentists, midwives, paramedics and traditional birth attendants divided by the population times 100,000

Household and Districts Characters Relationship

Variable relationship between Household and district characteristics on per capita household expenditure in Dodoma Region is shown conceptual framework in Figure 3.1 bellow.

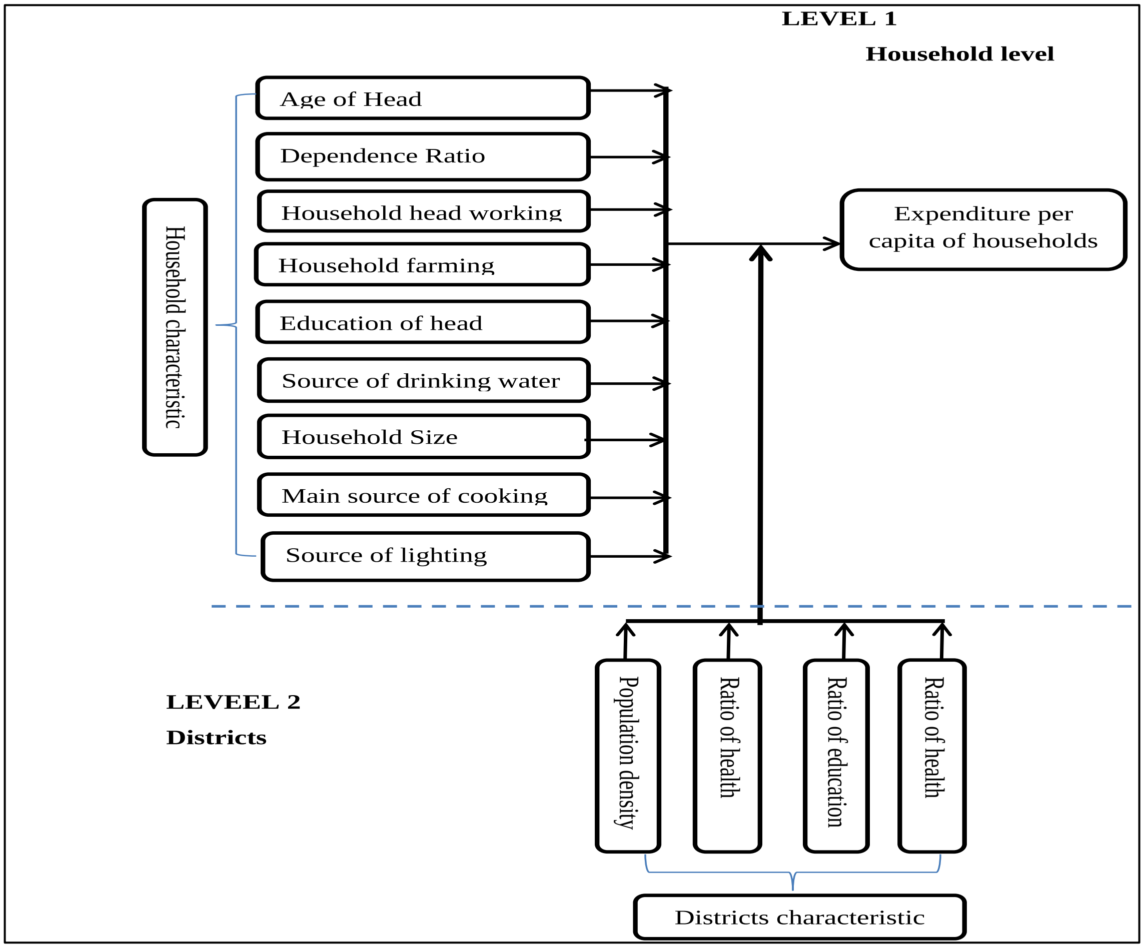

Figure 3.1 Conceptual Framework

3.2 Research Stage and Methods

Before carrying out the research stage, the data pre-processing stage will be processed as follow;

1. Prepare per capita expenditure data for each household in all districts of Dodoma from Household budget survey data of 2017/2018.
2. Prepare data for level 1 predictor variables per household from HBS microdata.
3. Prepare data for level 2 predictors variable (macro) per districts / city.
4. Combine data at stages 3 to stage 5 into data set.

The research methods and stages that will be carried out to achieve the research objectives are as follows;

1. Identify the variable that has influence or have a significant effect on the per capita household expenditure data per district.
    a) Exploring of response variable data (household per capita expenditure) through descriptive statistics
    b) Conduct the goodness of fits test on per capita household expenditure to check the distribution of data.
2. Modeling of per capita household expenditure with two-level LL3 hierarchical using Win BUGS involve the following;
    a) Forming the response vector in each district, y_j, $j = 1, 2, 3 \cdots 7$
    b) Forming level 1, **X** predictors matrices according to the Win BUGS format
    c) Forming level 2, **G** predictors matrices according to the Win BUGS format
    d) Determine the prior and hyper prior distributions of the parameter to be estimated.
    e) Create a Directed Acyclic Graph (DAG), a two-level hierarchical model
    f) Create the code program for a two-level hierarchical model
    g) Estimating the two-level model using MCMC and Gibbs Sampling
    h) Iterate the parameter estimation process until the equilibrium distribution is reached to get the parameter estimate characteristics. If until the iteration process is over, the equilibrium has not been reached, then an additional sample is performed.
    i) Evaluate the model using credible intervals. If there are insignificant predictors, then an alternative model is built by using these predictors
    j) Choosing the best model based on **DIC**
    k) Conducting an interpretation and conclusion.

3.3 Categorical Variable

When an indicator variable is used in regression, one of the indicator variables is left from the regression model. This indicator variable becomes the base or reference level to which the other levels are compared (Koop and Tobias, 2007).

In per capita household data, household farming, education level, source of drinking water, source of lighting, source of cooking and gender of the head are categorical variable which falls in the regression model, leaving out one observation with values of zero for the other values in categories.

In the regression results, the coefficient of an indicator variable represents the mean effect a true value of the indicator has on the dependent variable compared to the base level. The corresponding p-value indicates whether this mean effect is different from zero.

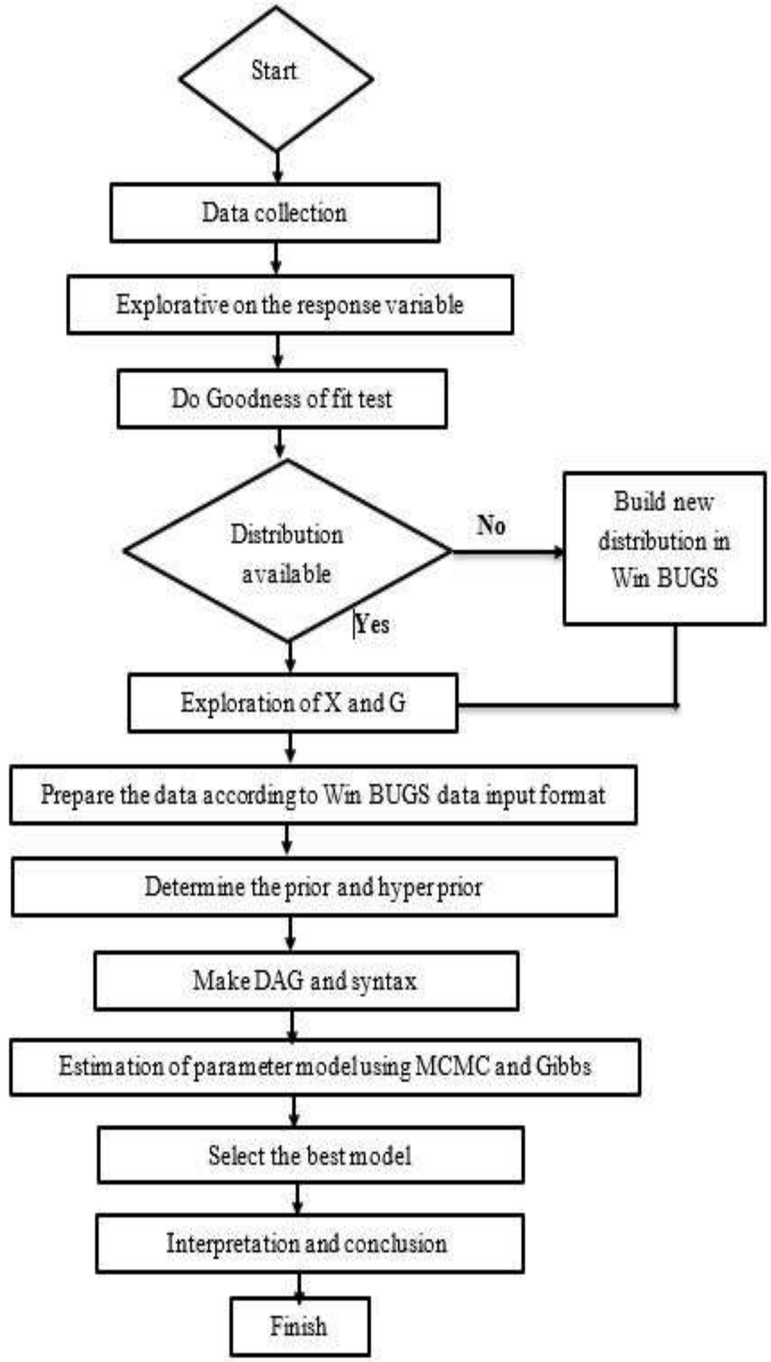

Figure 3.2 Diagram Show Gibbs Sampling

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CHAPTER 4
DATA ANALYSIS AND DISCUSSION

4.1 Explanatory Data Analysis

One of the indicator that influence per capita expenditure is number of member in the household, Figure 4.1, show mean per capita expenditure and household size in Dodoma region, the mean per capita is very high (TSH 94,037) in group with less than three people compare to household with number member more than three.

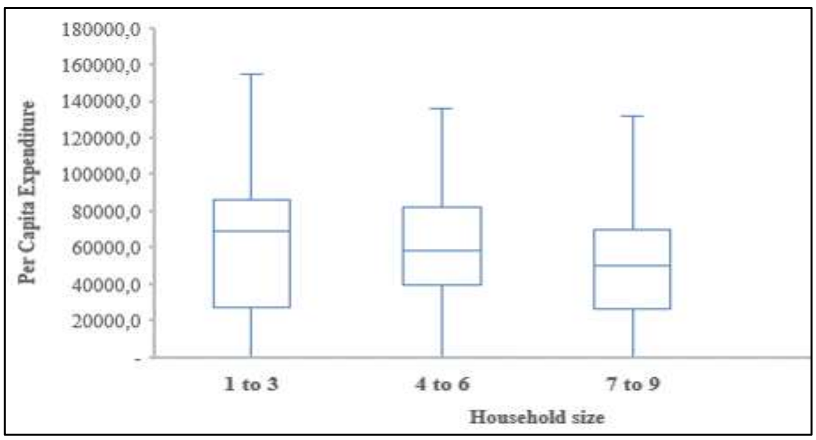


Figure 4.1 Household Expenditure and Size of household member

Table 4.1 Statistics for Per Capita Expenditure and Employment Status

	Mean	Minimum	IQR	Maximum
Employed	116 434	16 260	122 346	1 234 339
Unemployed	109 245	10 998	113 228	755 095

Although there is no significantly difference between employed and non-employed head of Household in Dodoma, household per capita expenditure is high with an average of TSH 116,434 per month more than these who are not employed with 109,2445.

4.2 Household Expenditure per Capita in Dodoma Region

Since 2017 the government decides to reallocate its office from Dar es salaam to the new capital city Dodoma. Dodoma region is located in the central part of Tanzania with seven districts, as one of the central parts of Tanzania, it has diverse geographical conditions. This diversity affects various fields of life, such as culture, social, economy, and even the level of welfare of the population.

The 2017-18 HBS revealed that the average expenditure of household per month in Dodoma reached TZS 416,927 Tsh, this value is still lower than the average national per capita expenditure which is TZS 356,357. However, this value is still quite high compared to other regions.

The comparison of expenditure per capita between districts in the Dodoma region has described in Table 4.2. The table shows that there are larger variations in the level of per capita expenditure among studied districts. Dodoma districts have the highest average per capita expenditure compared to other districts with quite large differences. The surprising observed in the Chemba districts which have the questionable average per capital expenditure.

Table 4.2 Descriptive Statistics of HHE per Capita Dodoma in 2018 (TZS).

Districts	**Mean**	**Coefficient of Variation**
Kondoa	85,251	56.32
Mpwapwa	144,566	132.94
Kongwa	98,414	81.09
Chamwino	70,855	69.31
Dodoma	170,794	79.76
Bahi	121,851	129.94
Chemba	62,587	38.66

In addition, the coefficient of variation shows a fairly low value. The results show that the expenditure per capita of the population in Dodoma municipality is quite evenly distributed among the population and therefore indicates the level of welfare is evenly distributed among the population. Meanwhile, the lowest per capita expenditure occurs in the Chemba with a coefficient of variation that is also small compared to other districts. The high coefficient of variation can reflect the gap in expenditure per capita between residents. Districts that have per capita expenditure characteristics that are similar to the Chemba are Kondoa and Chamwino, these are three districts with geographical conditions that are not much different.

Mpwapwa is the second-highest per capita expenditure district and the highest coefficient of variation in Dodoma region in 2018. This condition illustrates that although there are some residents who have high incomes, also a few of them have a much lower income. The coefficient value of the different variations between districts can reflect the gap in welfare between residents from the point of view of expenditure/income. The difference in welfare will be more clearly seen from the pattern of distribution of per capita expenditure data in each district.

4.3 Distribution of Per Capita HHE in Dodoma Region

Each district has unique characteristics of per capita expenditure data. The unique characteristic explained by knowing the distribution of the observed data. The Kolmogorov-Smirnov test as a goodness of fit test was used to determine the distribution of per capita expenditure data. The distribution results from the Kolmogorov-Smirnov test show that there is three suitable distributions for per capita expenditure data, namely Log-Logistic distribution, three-parameter log-logistic and three-parameter Lognormal.

The three distributions have characteristics that are in accordance with the characteristics of per capita expenditure data, which is the value of observations that are always positive. However, taking into account the p-value shown in Table 4.2, the most appropriate distribution for per capita household expenditure in all districts is Log-logistic three parameters. All distribution did not reject the null hypothesis at the level of significance but for the sake of limited time to finish this study, only log-logistic three-parameter was used to compare one level and two-level.

Table 4.3 Test Statistics and *p-value* Kolmogorov Test Result

Districts	Distributions		
	Log-Logistic	**Log-Logistic (3P)**	**Log-normal (3P)**
Kondoa	0.069 (0.989)	0.084 (0.942)	0.085 (0.937)
Mpwapwa	0.107 (0.603)	0.098 (0.705)	0.111 (0.554)
Kongwa	0.059 (0.976)	0.059 (0.972)	0.076 (0.853)
Chamwino	0.089 (0.815)	0.083 (0.871)	0.083 (0.873)
Dodoma	0.096 (0.509)	0.067 (0.887)	0.073 (0.825)
Bahi	0.154 (0.339)	0.125 (0.597)	0.191 (0.135)
Chemba	0.178 (0.179)	0.094 (0.881)	0.111 (0.722)

Note: The test statistics value obtained at a significant level $\alpha = 5\%$. The *p-value* is shown in the parenthesis

The three distributions have characteristics that are in accordance with the characteristics of per capita expenditure data, which is the value of observations that are always positive. However, taking into account the p-value shown in Table 4.2, the most appropriate distribution for per capita household expenditure in all districts is Log-logistic three parameters. All distribution did not reject the null hypothesis at the level of significance but for the sake of limited time to finish this study, only log-logistic three-parameter was used to compare one level and two-level.

Salem and Mount (1974) say that the log-logistic distribution is appropriate compared to the Log-normal distribution to describe population income data in the United States in the 1960s to 1969. While according to Alaiz and Victoria-Feser (1996) the log-logistic distribution has the advantage that its parameters can be directly linked to equality of expenditure. If the parameter α (shape parameter) is bigger, then the population with the lowest expenditure decreases, which means that expenditure in the area tends to be more evenly distributed. While parameter λ (threshold parameter) can describe the expenditure gap between district. With these considerations, the log-logistic distribution of the three parameters is considered as the most appropriate to describe the pattern of household per capita expenditure in the Dodoma Region.

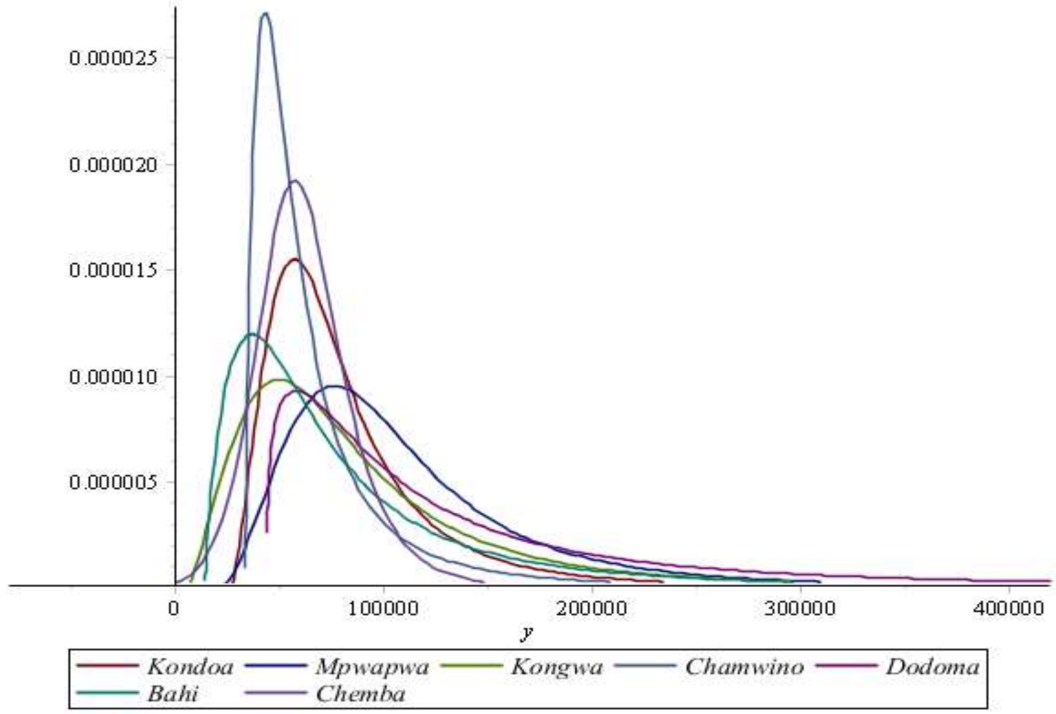


Figure 4.2 PDF Log-Logistic Three Parameter of Per Capita Household

Estimates of the Log-logistic distribution parameters of the three parameters are presented in Appendix 1 and illustrated graphically as in Figure 4.2.

It can be seen that the distribution of household per capita expenditure in each district of the Dodoma region does not seem to be balanced. There are expenditure groups on the left side of the plot with a long tail on the right side, this indicates a gap in expenditure per capita between households in each district. The distribution of household expenditure per capita in the Dodoma region shows the expenditure gap in Mpwapwa and Chamwino districts is very high compared to the other districts with the skewness of 4.6 and 3.8 respectively. Also, the shift in the form of distribution in Dodoma and Kongwa shows evenly distributed per capita expenditure compared to other districts. These districts have almost similar expenditure characteristics influenced by household characteristics and district characteristics.

4.4 Characteristic of Factors Influence Per Capita Household Expenditure

Table 4.3 presents a description of household characteristics that will be used as first-level predictors in the modeling of household per capita expenditure. The average age of household heads in Dodoma is 50 years. When viewed between districts, the average age of the head of the household is almost the same. However, the education level of the household head shows that there are variations between the districts of the city. The level of education of the household head, especially in Kondoa and Dodoma, is higher than in any other area. This portrait is shown with a high percentage of household heads with a minimum of primary school education. This indicates that most of the head of household has completed the primary level of education which is compulsory for the education system of Tanzania.

Based on the family engaged in agriculture Table 4.3 shows there are large differences in the percentage of households engaged in agriculture between Dodoma and other districts. The districts have the smallest number (58.6 %) lag behind Chemba with (100%), Chamwino, Mpwapwa and Kongwa with 97.9, 95.8 and 93.3 respectively. This is accompanied by the fact, the districts are with the highest population where most of the heads of households are employed and the rest are engaged in other business activities.

It can be viewed from the household characteristics that in general housing conditions in Dodoma is not good. More than half of the households at least 60 % of the household use other sources of light rather than electricity, this includes rechargeable lamps 43.2 % and solar power 25 % as their main source of light.

In addition to household characteristics, district characteristic is also used in modeling per capita expenditure household. A summary statistics of the characteristics of the city district is given in Table 4.5. Based on population density, there is an uneven distribution of the population in Dodoma.

Dodoma municipality has the highest population density, which is 192.42 km^2 / person. This condition is very much different from other districts, where population density is only in the range of 17 to 77 km^2 / person.

Table 4.4 Percentage of Households Characteristics by Districts, 2018

Districts	Age	Employment	Farming	HHS	Electricity	Water	EDL
Kondoa	54	56	91.7	3	5.6	50	72.2
Mpwapwa	47	31.2	95.8	3	6.2	87.5	54.2
Kongwa	51	63.3	93.3	4	23.3	15	43.3
Chamwino	53	37.5	97.9	4	4.2	47.9	56.2
Dodoma	47	71.4	58.6	4	42.9	15.7	67.1
Bahi	45	85.7	88.6	4	31.4	48.6	62.9
Chemba	58	69.4	100	4	0	25	61.1

In general, the ratio of education facilities (elementary, junior high and high school) Comparison of education facility availability against population also vary significantly in values between districts. Kondoa has the highest education facility ratio is reaching 436.74. While the lowest is in Kongwa with only 98 of education facility. The Health facilities and the ratio of health personnel are so important in order to build a strong economy with good health treatment.

The ratio of health personnel varies significantly from one district to others, Dodoma municipality has the highest ratio of a healthy person with 337 compared to other districts, Chemba the least one with 35.6.

Table 4.5 Districts Characteristic of Dodoma Region in 2018

Districts	Population density	Health facility	Education facility	Health person
Kondoa	17	16	436.74	72.59
Mpwapwa	41	20	110.00	128.50
Kongwa	77	17	98.00	117.43
Chamwino	54	16	112.25	80.89
Dodoma	192	18	128.16	337.84
Bahi	36	18	100.00	92.04
Chemba	32	16	100.00	35.64

4.5 Hierarchical Parameter Estimation of Per Capita HHE

In accordance with the definition of a two-level Bayesian hierarchical LLD3 model in chapter 2, if the random variable Y is distributed as follows;

$Y \sim LL3(\mu_{[y]}, \sigma_{[y]}, \theta)$ then the Bayes hierarchy model is called the Bayesian hierarchy model based on LLD3 distribution. The two-level Bayesian model with this LLD3 is the DAG of the model in Figure 4.3. This DAG illustrates the behavior of the relationship between data and parameters inside the model. According to the Bayesian method conceptual, DAG illustrates the relationship between the data used, parameters and hyperparameters in the model and prior distribution.

Oval nodes indicate stochastic parameters and box nodes indicate constant values. The parameters $(\mu_{[y]}, \tau_{[y]})$ and θ in the DAG are location, precision and boundary parameters of the LLD3 distribution as well $\tau_{[y]} = 1/\sigma_{[y]j}$. The LLD3 hierarchy model likelihood functions if $Y \sim LL3(\mu_{[y]}, \sigma_{[y]}, \theta)$ and $\tau_{[y]} = 1/\sigma_{[y]j}$ are precision parameters, then Y will follow the PDF based on the equation (2.22). If Y is

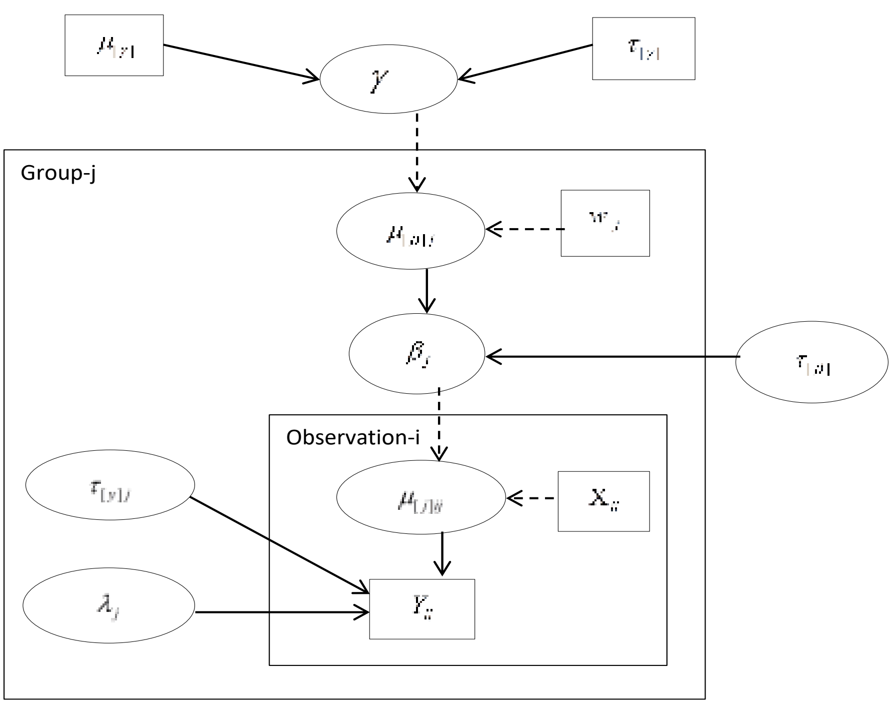


Figure 4.3 DAG Two-level HM Based on Three-Parameters LLD Distribution

a random variable that comes from seven districts as in the study, then we can obtain the vector $y=\left[y_1, y_2, \ldots, y_7\right]^T$ and $y_j=\left[y_{j1}, y_{2j}, \ldots, y_{n_j j}\right]^T$, $j=1,2,\ldots,7$ and $\sum_{j=1}^{m} n_j = N$. Jenkins (2005) and Zorn (2007) states that if $Y \sim LL3\left(\mu_{[y]}, \sigma_{[y]}, \theta\right)$ then $\left(Y-\theta\right) \sim Logistics\left(\mu_{[y]}, \sigma_{[y]}\right)$. Next if given $x_{ij}^T=\left[1, x_{1ij}, x_{2ij}, \ldots, x_{11ij}\right]^T$ and given $E\left(\ln\left(y_{ij}-\theta_j\right)\right)=\mu_{[y]j}$ then $\mu_{[y]j}=x_{ij}^T\beta_j$ according to the DAG model of the two-level hierarchy in Figure 4.5, the likelihood function of y is stated as follows:

$$f_L\left(y/\mu_{[y]}, \tau_{[y]}, \theta\right)=\prod_{j=1}^{m}\prod_{i=1}^{n_j} f_L\left(y_{ij}/x_{ij}^T\beta, \tau_{[y]j}, \theta_j\right)$$

$$\prod_{j=1}^{m}\prod_{i=1}^{n_j}\frac{\tau_{[y]j}\left\{\exp\left[\tau_{[y]j}\left(\ln\left(y_{ij}-\theta\right)-x_{ij}^T\beta\right)\right]\right\}}{\left(y_{ij}-\theta_j\right)\left\{1+\exp\left[\tau_{[y]j}\left(y_{ij}-\theta_j\right)-x_{ij}^T\beta\right]\right\}}$$

$$=\prod_{i=1}^{n_j}\frac{\tau_{[y]j}\left\{\exp\left[\tau_{[y]j}\sum_{i=1}^{n_j}\left(\ln\left(y_{ij}-\theta\right)-x_{ij}^T\beta\right)\right]\right\}}{\left(\prod_{i=1}^{n_j} y-\theta_j\right)\left\{1+\exp\left[\tau_{[y]j}\sum_{i=1}^{n_j}\left(y_{ij}-\theta_j\right)-x_{ij}^T\beta\right]\right\}^2}$$

$$\prod_{i=1}^{n_j}\frac{\prod_{j=1}^{m}\tau_{[y]j}\left\{\exp\left[\sum_{j=1}^{m}\tau_{[y]j}\sum_{i=1}^{n_j}\left(\ln\left(y_{ij}-\theta\right)-x_{ij}^T\beta\right)\right]\right\}}{\left(\prod_{j=1}^{m}\prod_{i=1}^{n_j}\left(y_{ij}-\theta_j\right)\right)\left\{1+\exp\left[\tau_{[y]j}\sum_{i=1}^{n_j}\left(y_{ij}-\theta_j\right)-x_{ij}^T\beta\right]\right\}^2} \tag{4.2}$$

Accordingly, the form of the micro model equation of the bayesian hierarchy model is two-level based on LLD3 distribution which follows equation (2.1). While the equation of the macro model of the hierarchy model follows equation(2.3),

4.5.1 Prior Distribution of LLD3 Hierarchy Models

The determination of the prior and hyper prior distribution of the hierarchy model is based on the hierarchical structure of the model parameter. In accordance with the hierarchical structure of the parameters, the parameters and hyperparameters which will be estimated in the formation of the two-hierarchy model are p, $\tau_{[y]}, \tau_{[\beta]}$, θ, β and γ. The prior and hyper prior distributions will be used in the hierarchy model based on the LLD3 distribution this is also a distribution prior and independent hyper priority. If the parameter that will be estimated is p, $\tau_{[y]}, \tau_{[\beta]}, \theta, \beta$ and γ then the prior distributions are of nature independent. Furthermore, the prior and hyper prior distributions that will be used in modeling based on LLD3 distribution consist of a combination of informative and pseudo priors. Based on the results of the elaboration and exploration carried out on the data, then the prior distribution is used for each parameter vector element $\tau_{[y]}, \tau_{[\beta]}, \theta, \beta$ and γ

4.5.2 Posterior Distribution of the LLD3 Model

After obtaining information on the likelihood data, prior distribution and hyper priority parameter distribution, then a combined posterior distribution is formed. The process of parameter estimation with the Bayesian approach is based on the posterior distribution of the parameter. The combined posterior distribution of all parameters that have been estimated is done using a combination of likelihood and prior. In the Bayesian Hierarchical LL3 modeling the posterior distribution obtained from the likelihood multiplication results and the prior distribution is as stated in equation 2.10.

4.6 Implementation of Two-Level Bayes Hierarchy on Per capita HHE

Implementation of two-level Bayes Hierarchy model for household per capita expenditure data in the Dodoma Region is carried out using eleven (k = 11) characteristics of households as predictors of micro and four (4) regional characteristics as a macro predictor. Modeling is done using the LLD3 distribution and model specifications as in equations (2.1) and (2.3). The visualization of the modeling process is illustrated through DAG in Figure 4. 2 with the distribution pattern of per capita household expenditure for each district the same, namely the distribution of LLD3.

The estimation process is carried out using WinBUGS software with 50,000 times iteration and thin 10. In the process of estimating the hierarchy model based on the LLD3 distribution, it requires a burn-in period of the first 100 iterations. Many iterations needed for the burn-in period are due to the complexity of the model. Thus the samples obtained to estimate the characteristics of the parameters were 49,900 samples. The results obtained from the parameter estimation process using MCMC and Gibbs Sampling show that the estimation process is carried out it fulfills the nature of MCMC and achieves convergent conditions. This conclusion is drawn based on the indications shown by the MCMC diagnostic plot which consists of trace and serial values of each parameter iteratively estimated, autocorrelation and quantile plot parameters.

4.6.1 Alternative Model 1:

Estimate involve all predictors at level 1 and level 2, On level 1 it produces 196 parameters and in level 2 as many as 108 parameters, which is most of them show compatibility with MCMC properties, namely irreducible and aperiodic. One of the examples is shown through the MCMC diagnostic plot in the parameter $\beta_{1,2}$ as follow:

1 Serial Plot of 49,900 samples was generated, it appears that the sample is generated in the MCMC process does not show extreme values or in other words, the serial plot parameters do not show a certain pattern, tend to be stationary and random.

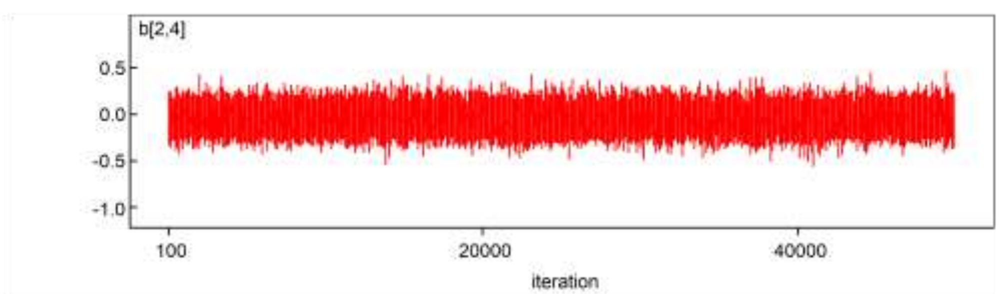


Figure 4.4 Serial Plot Parameter Estimation of $\beta_{1,2}$.

2. Figure 4.5 confirm the sample obtained has a very small autocorrelation value close to 0. The results indicate that the sample generated through the MCMC process has a random nature.

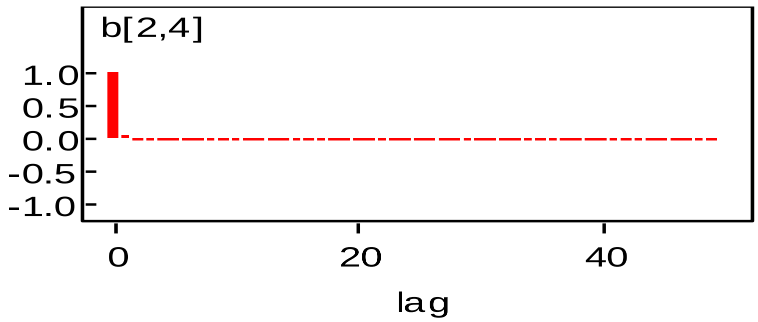


Figure 4.5 Autocorrelation Plot Parameter Estimation of $\beta_{1,2}$.

3. The Posterior density plot Figure 4.6 for parameter shows a pattern that is similar to the prior distribution pattern used for that parameter, For example, the prior distribution used for one of the slope macro models is normally distributed and the posterior density function plot is shown by Figure 4.6. The normality test using Kolmogorov-Smirnov states that the sample obtained is indeed in the normal distribution

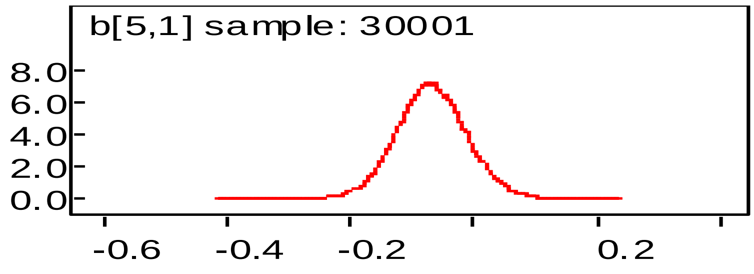


Figure 4.6 Quantile Plot Parameter Estimation of $\beta_{1,2}$.

According to the MCMC diagnostic plot which displays the trace, serial, autocorrelation, and quantiles plot. It is concluded that the parameter estimation process that has been carried out has reached a convergent condition. Thus, the estimated parameter generated can be used to describe the hierarchical model on household per capita expenditure in Dodoma Region. The estimation of the parameters of the two-level hierarchy model that contains the micro and macro models is carried out simultaneously. A posterior summary of all parameters in the two-level hierarchy model on household per capita expenditure is given in Appendix 6 to Appendix 8. The summary of the micro model regression coefficient in all seven districts is shown in Table 4.6. The parameters significance test in the two-level hierarchy model was done by using WinBUGS credible intervals.

If the credible interval contains zero, then it is concluded that the parameter estimate is not significant. Based on Table 4.5 it can be seen that the regression coefficient of the micro model which is not significant in almost all regencies of the city are β_1, $\beta_{4,1}$, $\beta_{4,3}$ and $\beta_{8,3}$. This means that the age of the household head, education level, and Male headed household does not significantly influence household expenditure per capita in Dodoma. Also In Table 4.5 shows that there exist differences and variations in the regression coefficients of the micro model across the districts, for example in the intercept coefficient, the largest value is in Kongwa districts and the lowest is in the Dodoma municipality. Intercept values in the two regions show considerable differences vary in the other five regions, As one example, the micro model for Kongwa district can be written as follows:

$$\hat{y} = 58.31 + 0.009x_1 + 0.255x_{2,1} - 0.519x_{3.1} + \cdots + 0.3559x_{25.1} + 0.1126x_{26.1} + 0.6849x_{27,1} \qquad (4.51)$$

Regarding to the equation (4.51), the regression coefficients which were significant in Kongwa districts were seven. These regression coefficients $\beta_{2,1}, \beta_{4,2}$, $\beta_{6,6}, \beta_{7,1}, \beta_{7,2}, \beta_{7,3}$,and $\beta_{13,1}$ which are associated with Haousehold head working, household member, Gas as energy source of cooking , Charcoal for cooking, Wood as sources of cooking, Electricity as source of light and Ox plough as asset owned respectively.

Table 4.6 Summary of Regression Model for Micro-Regression Coefficients

Coefficient	Kondoa	Mpwapwa	Kongwa	Chamwino	Dodoma	Bahi	Chemba
β_0	-103.70*	37.7500*	58.310*	-37.9600*	11.930*	12.510*	-31.9600*
β_1	-0.0076	0.0035	0.0085	0.0003	0.0060	0.0153	-0.0056
$\beta_{2.1}$	-0.0443	0.0349	0.2554*	-0.0724	0.1189	0.1570	0.0434
$\beta_{3.1}$	-0.0769	-0.6380	-0.5188	0.4158	-0.1200	-0.8124	50.480*
$\beta_{4.1}$	0.1202	0.0925	0.0528	0.0643	0.0914	-0.2010	0.0168
$\beta_{4.2}$	-0.0689	-0.1181*	-0.109*	-0.1067*	-0.141*	-0.209*	-0.1487*
$\beta_{4.3}$	48840	27100	0.0000	23790	0.0000	22180	17130
β_5	113.700*	-33.770*	0.3080	19.4700	-0.4259	0.5396	-33.4200
$\beta_{6.1}$	113.900*	-33.570*	0.6786	19.3800	-0.2020	0.1474	-33.9200
$\beta_{6.2}$	48700.00	-33.02*	-0.07	23790.00	383.10*	1.62	-33.48
$\beta_{6.3}$	48920.00	27160.00	0.62	-264.30*	0.20	-0.01	-33.02
$\beta_{6.4}$	113.900*	-33.190*	1.0380	19.600	-0.2577	1.7880	-32.9900
$\beta_{6.5}$	1.55	27100.00	29980.0	28.86*	-0.24	22330.0	-99.75
$\beta_{6.6}$	-621.60*	-23.07*	-47.53*	23690.00	0.00	-2.70	16970.00
$\beta_{7.1}$	1.460	9.043	-47.22*	23800.000	-0.071	-1.923	-99.420*
$\beta_{7.2}$	1.4890	9.6570	-47.83*	29.8600*	-0.2519	-1.2020	-99.800*
$\beta_{7.3}$	0.1682	-2.0770*	0.4297	-0.6213	-0.0481	0.0900	126.400*
$\beta_{7.4}$	0.7266	-1.9530*	0.9460*	283.1000*	-0.2982	-0.3306	126.0000*
$\beta_{8.1}$	48820.00	-1.860	0.308	-0.581	-383.7*	-1.363	126.600*
$\beta_{8.2}$	0.1644	-1.949*	0.2835	-0.6231	-0.2705	-0.1233	126.40*
$\beta_{8.3}$	-0.2591	0.1251	-0.0626	0.0577	0.2843	0.3117	0.2445
$\beta_{8.4}$	623.900*	26850.000	0.632	23770.000	-0.070	1.955*	17280.00
$\beta_{9.1}$	-0.1922	0.0755	-0.1792	0.0731	0.0263	0.0666	-0.0941
$\beta_{10,1}$	48880	-0.6432	0.4356	0.6438	0.1548	1.5860*	16960
$\beta_{11,1}$	48990	27020	0.3559	23460	0.4016	-2.861*	17000
$\beta_{12,1}$	0.2207	0.1698	0.1126	0.2172	-0.1536	-0.2464	0.2173
$\beta_{13,1}$	0.1035	0.2603	0.6849*	0.4578*	-0.1290	0.1439	-0.1166

Note:* The parameter coefficients values obtained at $\alpha = 5\%$ level of statistically significant
β_i indicate estimate ($\hat{\beta}_i$) of the Household characters where i = 1, 2, 3, … , 27

The predictors are significantly influence the per capita expenditure of household in Tanzania at Kongwa district. However the unexpected results was observed in twenty parameters coefficient of regression in Kongwa district at micro level which appear to be insignificant on household per capita expenditure. The variation of the regression coefficient is more visible if visualized in a graphical way with Boxplot. Figure 4.7 provides an illustration of the variations in the regression coefficient model micro, namely the source of water in the household. The variation of the regression coefficient of the micro model shows that Mpwapwa has the largest average value (boxplot image with the symbol [7,2]). While the region with the average smallest value is Dodoma districts[7,5]. Boxplots that illustrate the variation in all micro model regression coefficients are given in full in Appendix 5.

The summary of the estimated results of the macro model parameters is presented in Table 4.6. Based on the results displayed, it is concluded that all the characteristics of districts significantly influence household expenditure per capita. The results indicated by credible intervals that do not contain zero values (Appendix 7) on several predictors of districts characteristics.

In the modeling hierarchical per capita expenditure in Dodoma, the combined cross-section model was formed for the two-level as in the equation (2.3). The cross-level interaction is a consequence of the variation of the micro slope model, this Cross-level interaction states the contextual relationship between household characteristics as a micro predictor and level of per capita household expenditure. Thus the cross-level interaction coefficient regression illustrates that if there are two households that have the same household characteristics but come from different districts, then it give different effect on the per capita expenditure.

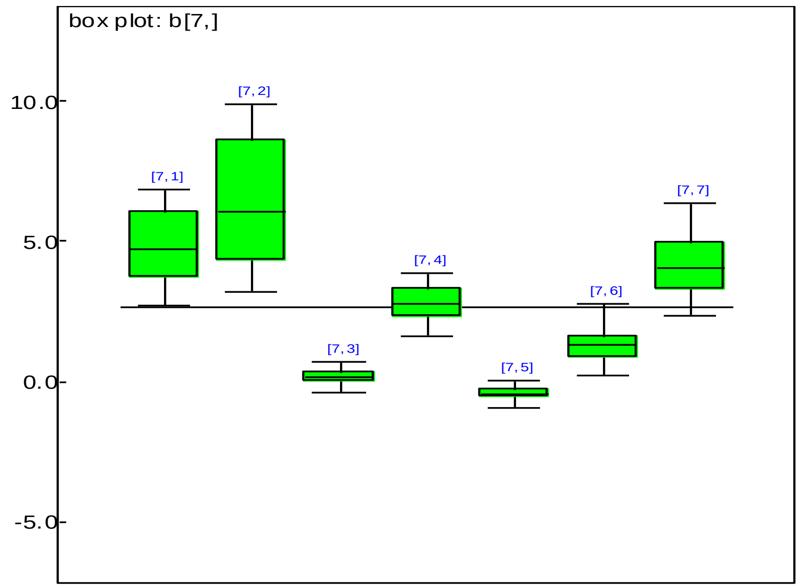


Figure 4.7 Posterior Mean Regression Coefficient for Source of Water.

Thus, the condition of districts as a macro predictor becomes moderator effect in the relationship between the level of per capita household expenditure and the district characters as explained by Hox (1995). Therefore, interpretations obtained from the influence of each predictor at micro-level of the hierarchical model are adjusted to the context of the conditions of each district. Contextually, the relationship between district characters and per capita household expenditure observed from the regression coefficient value of the interaction between micro predictors and macro predictors.

Based on the three parameter log logistic with ten micro predictors and four macro predictors the estimation of the parameters produces seven micro regression models as in equation (10) that illustrate the effect of household characteristics on per capita expenditure for each household and the combined cross-section model of level-2 can be written as follow;

$$\hat{\beta} = 88 + 89.97\lambda_1 + 89.99\lambda_2 + 87.9\lambda_3 + 89.96\lambda_4 \qquad (4.52)$$

Based on the equition (4.52), we observe that there are little variations in the significant of parameters among districts. All regression parameters obtained in macro level model were statistical significantly at 5% level. This indicates that our four macro explanatory variables were higly influence the per capital expenditure among all districts.

Besides, all estimated parameter of the district predictors was significant, the same results were obtained under log logistic model from the study of [12]. It means that the four districts predictors affect on per capita household expenditure in Dodoma region. Nevertheless, the estimated value of the models seems very close to each other. This results indeed supported by the previous study of [10]. The small variation of the significant macro coefficient suggests the difference in per capital household expenditure is due to household characteristics and not districts characters. Therefore, among the macro predictors there is no variable which has highly dominant influence to the household per capital expenditure compared to others in Dodoma region. Those four explanatory variable are population density, ratio of health facility per 100,000 populations, ratio education facility per 1000 school age-population and ration of health person per 100,000 populations.

Table 4.7 Summary of Regression Model for Macro-Regression Coefficients

Coefficient	Kondoa	Mpwapwa	Kongwa	Chamwino
β_0	89.97	89.99	89.94	89.96
β_1	89.99	90	89.93	89.94
$\beta_{2.1}$	89.98	89.99	89.96	89.96
$\beta_{3.1}$	89.98	89.99	89.95	89.97
$\beta_{4.1}$	89.99	89.98	89.95	89.96
$\beta_{4.2}$	90	90	89.98	89.98
$\beta_{4.3}$	89.96	89.98	89.95	89.97
β_5	89.99	89.99	89.95	89.96
$\beta_{6.1}$	89.98	89.99	89.97	89.97
$\beta_{6.2}$	89.99	90	89.97	89.96
$\beta_{6.3}$	89.98	89.99	89.94	89.97
$\beta_{6.4}$	89.99	89.99	89.94	89.97
$\beta_{6.5}$	89.97	89.99	89.94	89.96
$\beta_{6.6}$	89.98	90	89.95	89.96
$\beta_{7.1}$	89.98	90	89.94	89.95
$\beta_{7.2}$	89.98	90.01	89.97	89.96
$\beta_{7.3}$	89.98	89.99	89.95	89.97
$\beta_{7.4}$	89.99	90	89.97	89.96
$\beta_{8.1}$	89.98	89.99	89.94	89.97
$\beta_{8.2}$	89.99	89.99	89.94	89.97
$\beta_{8.3}$	89.97	89.99	89.94	89.96
$\beta_{8.4}$	89.99	90	89.97	89.96
$\beta_{9.1}$	89.98	89.99	89.94	89.97
$\beta_{10,1}$	89.99	89.99	89.94	89.97
$\beta_{11,1}$	89.99	90	89.97	89.96
$\beta_{12,1}$	89.98	90	89.94	89.95
$\beta_{13,1}$	89.98	90.01	89.97	89.96

Note:* The parameter coefficients values obtained at $\alpha = 5\%$ level of statistical significant. The λ_i indicate estimate of the Household characters where i = 1, 2, 3, and 4

4.6.2 Alternative Model 2:

Alternative model 2 prepared using all predictors variable to estimate parameters model at one level, all predictors related to household and four district characteristics were used at the same level to estimate the model. For instance, the MCMC diagnostic plot in the parameter β_1 and $\beta_{2,1}$ are displayed as follows.

1 Autocorrelation (ACF) plot for parameter β_1 and $\beta_{2,1}$ is shown in Figure 4.8, based on the ACF plot results which are formed its shows the evidence that the sample parameter estimates are random. This is shown through autocorrelation which is worth one in lag 0 and zero or close to zero in other lags.

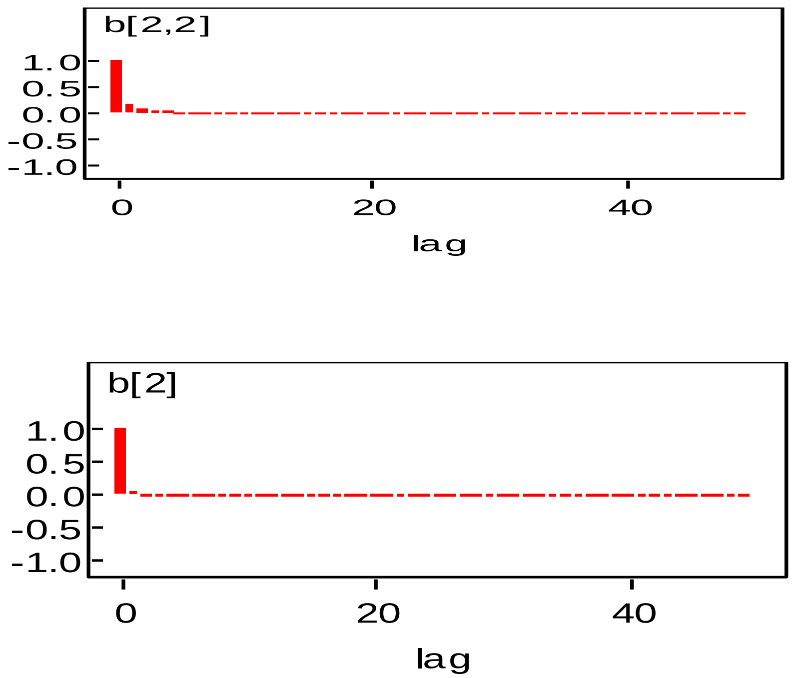
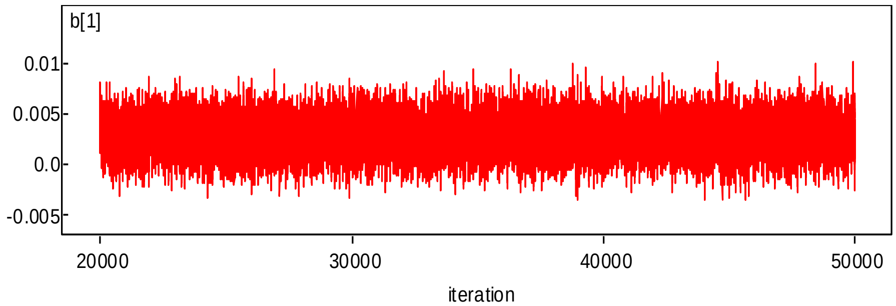


Figure 4.8 Autocorrelation Plot Parameter Estimation of β_1 and β_2

2 Serial Plot of 49,900 samples was generated, it appears that the sample is generated in the MCMC process does not show extreme values or in other words, the serial plot parameters do not show a certain pattern, tend to be stationary and random see in Figure 4.8.

3 The Quantile plot Figure 4.9 shows the ergodic mean of parameter β_1 and β_2 obtained has reached a stable value and is in a credible interval. This indicates that the parameter estimates are generated from the process that has reached equilibrium or convergent see in Figure 4.9.



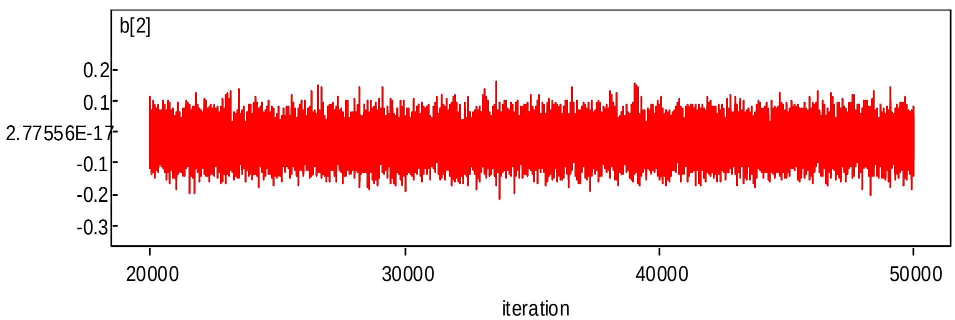
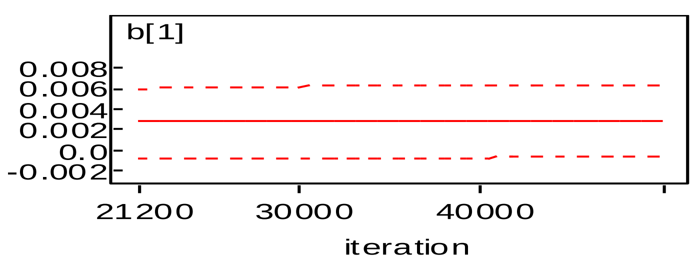


Figure 4.9 Serial Plot Parameter Estimation of β_1 and β_2



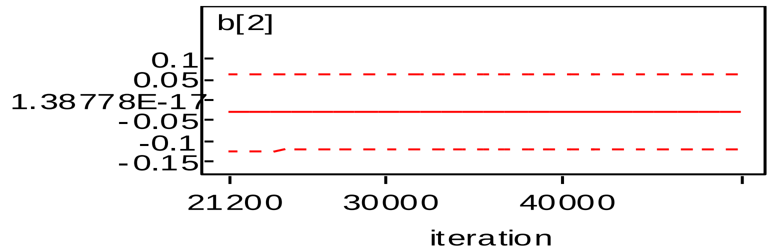


Figure 4.10 Quantile Plot Parameter Estimation of β_1 and β_2.

Based on MCMC diagnostic plots which are trace, serial, autocorrelation, posterior estimates of all parameters in alternative model 2 are given in Appendix 10 through Appendix 12 are the summary of the regression coefficients of micro models in all districts shown in Table 4.7. It is noted that only five ($\beta_{3,1}$, $\beta_{4,1}$, $\beta_{4,2}$, $\beta_{10,1}$, $\beta_{11.1}$,) out of twenty-seven of the regression coefficient are significant. This means that the head household working involved in farming, household size and Education level of head significantly influence household expenditure per capita in Dodoma.

For instance, in the fouth row of the Table 3, the alternative model I parameter $_3$ indicates the fourth regression parameter and its mean, MCM error, and median are -0.2070; 0.00084; and -0.2078 respectively. The mean indicates the significance of the parameters as it lies within the credible interval (2.5% to 97.5%) that stratches from -0.40980 to -0.00412 and the same way illustrated for the fith, six, twenty three and twenty four parameters.

Table 4.8 Summary of Regression Coefficients in One-Level Bayesian Model

Coefficient	**Mean**	**MCM error**	**2.5%**	**Median**	**97.5%**
β_0	11.1700*	0.0089	10.5300	11.1800	11.7700
β_1	0.00280	0.00002	-0.00068	0.00279	0.00629
$\beta_{2,1}$	-0.0294	0.00026	-0.12030	-0.0295	0.06301
$\beta_{3,1}$	-0.2070*	0.00084	-0.40980	-0.2078	-0.0041
$\beta_{4,1}$	0.10600*	0.00034	0.04291	0.10600	0.16980
$\beta_{4,2}$	-0.1155*	0.00011	-0.14460	-0.1155	-0.0865
$\beta_{4,3}$	-0.0523	0.00129	-0.37870	-0.05398	0.28450
β_5	-0.1896	0.00145	-0.44910	-0.1894	0.07154
$\beta_{6,1}$	0.02127	0.00136	-0.23380	0.02228	0.27540
$\beta_{6,2}$	0.00278	0.00146	-0.33100	0.00337	0.33790
$\beta_{6,3}$	0.27710	0.00144	-0.04164	0.27690	0.59860
$\beta_{6,4}$	0.09468	0.00136	-0.19860	0.09374	0.3885
$\beta_{6,5}$	0.08814	0.00672	-0.50290	0.07862	0.7335
$\beta_{6,6}$	0.69110	0.00671	-0.00194	0.68310	1.4200
$\beta_{7,1}$	0.30410	0.00654	-0.14960	0.29330	0.8391
$\beta_{7,2}$	0.15600	0.00684	-0.3222	0.14500	0.7036
$\beta_{7,3}$	-0.0363	0.00120	-0.2883	-0.0357	0.2168
$\beta_{7,4}$	0.07718	0.00144	-0.19670	0.07577	0.3550
$\beta_{8,1}$	-0.04408	0.00149	-0.43560	-0.04269	0.3383
$\beta_{8,2}$	-0.05939	0.00128	-0.31400	-0.05919	0.1937
$\beta_{8,3}$	0.11260	0.00040	-0.01060	0.11250	0.2354
$\beta_{9,1}$	0.10900	0.00083	-0.18190	0.10970	0.3948
$\beta_{10,1}$	0.17760*	0.00041	0.05078	0.17760	0.30420
$\beta_{11,1}$	0.17690	0.00104	-0.14930	0.17790	0.50050
$\beta_{12,1}$	0.08740	0.00041	-0.03923	0.08728	0.21370
$\beta_{13,1}$	0.1876	0.00052	0.02807	0.1879	0.34510

4.6.3 Selection of the Best Model

Modeling per capita expenditure of households in Dodoma was conducted with two alternative models. The first model includes parameter estimation using two-level hierarchical with household characteristics at the first level and district characteristics at the second level while the second model involves estimation using only one level without distinguishing between household and districts characteristic. Table 4.8 below presents the DIC values used as a measure of the best model of goodness.

Table 4.9 Goodness of Fit Test

Model	DIC
Alternative I	801
Alternative II	1070

Based on Table 4.8 it is known that the model with the smallest DIC is the best model to model per capita household expenditure, by considering the value of the DIC, it can be concluded that the first alternative model is better than the second alternative model.

4.7 Effect of HH and District Characteristics on Per Capita Expenditures

From the discussion above it can be concluded that, the selection of the best model with the values of DIC shows that the first alternative model is better than the second. In this section, the hierarchical log-logistic model is discussed to examine the effect of household and district characteristics on household per capita expenditure in Dodoma region.

In the discussion of the previous sub-chapter 4.5.1, the first alternative model has several parameters that have been shown to be significant. Therefore, this section will only discuss the significant influence characteristics in Kongwa district on per capita expenditure in Dodoma.

Per capita household expenditure is largely influenced by employment status ($\beta_{2,1}$**)**, expenditure double in the household where the head is employed compare to these who are not employed. The change also apply to the ownership of property where household with ox-plough ($\beta_{13,1}$) spend more than that of those without.

The source of energy (β_7 **)** also plays a crucial role in the household per capita expenditure, the household using electricity as the main source of energy for cooking spend more than household whose use other source of enegy.

The situation of the districts as a macro predictor becomes a moderator effect in the relationship between the level of per capita household expenditure and household characteristics. The interesting of the macro model is that all the predictors variable are significantly explaining the relationship between household characteristics and per capita household expenditure

CHAPTER 5
CONCLUSION AND RECOMMENDATION

5.1 Conclusion

Based on the results of this study, modeling of per capita household expenditure using the two-level hierarchy model with the Bayesian approach the following conclusions are obtained:

1 Per capita household expenditure in each district in Dodoma shows unique characteristics, the value of per capita household expenditure is always positive with a minimum value never equal to or smaller than zero. Therefore appropriate distribution for household expenditure per capita is the Log-logistic distribution.

2 The results of the implementation of the two-level hierarchy model based on the three-parameter log-logistic distribution on household per capita expenditure in Dodoma showed variations in the regression coefficients of micro models between districts. This variation is proven to be significantly influenced by both household and district characteristics, However, the magnitude of influence of household characteristics cannot be generally applied to households in Dodoma Region. Thus, a two-level hierarchical Bayesian model is able to illustrate the effect of predictors at different levels on household per capita expenditure.

3 The model per capital expenditure in Dodoma region was successful built, however three factors are not relevant. Therefore the more study is needed to find out if these factors are critical problem in the welfare of the people in Dodoma region

5.2 Recommendation

Taking into account the results of this study, a number of suggestions can be recommended as follows:

1. One of the limitations in the present study is focusing only two level hierarchical log logistic distribution. In further research the suggestion provided to improve

modeling of this field by adding levels in the hierarchical model to see the effect of three levels in improving the results in order to establish rational policies that are indeed based on regional characteristics

2. The use of the Bayes method involves decide on what prior and prior value to use therefore researchers should pay attention when they design to employs Bayes methods in modelling per capital expenditure due to its complexity nature of using different prior distribution and prior value. In line with that, researchers should have enough knowledge in the usage of different package of software since the completion of reasonable and sound analysis incorporate more than two applications to complete analysis and obtain reflect results.
3. Several factors that are essential to influence household per expenditure are excluded due to luck of data availability and time constraints such as dependence ratio, road accessibly, and Gross domestic product per districts. Therefore, in the future study more variables should be considered to prevailing the detail reputation and behavior of Households' welfare in Dodoma region.
4. For our best knowledge our model is strongly statistically significant. Therefore, Information on grouping districts in Dodoma Region in this study can serve as additional information for other purposes such as the implementation of command programs related to household welfare in each districts.

REFERENCES

Ajibade, B., & Ukponmwan, N. (2017). Evaluation of Techniques for Univariate Normality Test Using Monte Carlo Simulation. *American Journal of Theoretical and Applied Statistics*, 51-61.

Ando, T. (2014). *Bayesian Model Selection and Statistical Modeling.* Kanagawa, Japan: Chapman & Hall.

Atkinson, A., & Lugo, M. (2010). Growth, poverty, and Distribution in Tanzania. *International Growth Centre*, 6-20.

Balakrishnan, N., & Norman, J. (1995). *Continuous Univariate Distributions.* New York: A Wiley-Interscience Publication.

Byaro, M., Kinyondo, A., Michello, C., & Musonda, P. (2018). Determinants of Public Health Expenditure Growth in Tanzania: An Application of Bayesian Model. *African Journal of Economic Review*, 3-10.

Casella, G., & George, E. (1992). Explaining the Gibbs Sampler. *American Statistical Association*, pp 167-174.

Chaudhry, I. S. (2009). The Impact of Socioeconomic and Demographic Variables. *The Lahore Journal of Economics*, 39-68.

Gelman, A., Carlin, J., & Stern, H. (2008). *Bayesian Data Analysis Third Edition.* USA: CRC Press.

Geyer, C. (2004). Introduction to Markov Chain Monte Carlo. In S. Brooks, & A. Gelman, *Handbook of Markov Chain Monte Carlo* (pp. 3-47). New York: CRS Press.

Gill, J. (2003). Hierarchical Linear Models. *Encyclopedia Social Measurements*, 50-57.

Goldstein, H. (1995). *Multilevel statistical models.* London: 1999.

Goldstein, H. (2010). *Multi-level statistical model.* Briston, UK: Walter A Shewhart and Samwel Wilks.

Grosh, M., & Baker, J. (1995). Proxy means tests for targeting social programs. *LSMS*, 20-36.

Haughton, J., & Khandker, S. (2009). *Handbook on Poverty and Inequality*. Washington, DC 20433: The World Bank.

Hogg, R., & Mckean, A. (2005). *Introduction to Mathematical Statistics.* USA: Pearson Education Inc.

Irawati, I. (2015). *Modeling of Per capita household in Maluku using structure hierarchical two-level Bayesian approach.* Surabaya: Institut Teknologi sepuluh Nopember.

Iriawan, N., Devi, S., & Yasmirullah, P. (2019). An Economic Growth Model Using Hierarchical Bayesian Method. *Bayesian Networks - Advances and Novel Applications*, 1-17.

Ismartini, P., & Iriawan, N. (2013). Model Criticism for Log-Normal Hierarchical Bayesian. *Model Criticism for Log-Normal Hierarchical Bayesian*.

King, R., & Morgan, B. (2010). *Bayesiana Analysis for Population Ecology*. USA: Chapman & Hall.

Koop, G., & Tobias, J. (2007). *Bayesian Econometric Methods.* New York: Cambridge University Press.

Kruschke, J. K., & Vanpaemel, W. (2015). The Oxford Handbook of Computational and Mathematical Psychology. *Bayesian estimation in hierarchical models*, pp.279-299.

Lunn, D., & Andrew, T. (2000). WinBUGS – A Bayesian modeling framework: Concepts, structure, and extensibility. *Statistics and Computing*, 325-337.

Lynch, S. M. (2007). *Introduction to Applied Bayesian Statistics and Estimation for Social Scientists.* New York: Springer.

MoF, & NBS. (2016/17). *Tanzania Five Year Development Plan 2016/17-2020/21 (FYDP II).* Dar es Salaam: MoF.

NBS. (2018). *Household and budget survey 2017/2018.* Dodoma: National Bureau of Statistics(NBS).

Ntzoufras, L. (2009). *Bayesian Modeling Using WinBUGS.* New Jersey: John Wiley & Sons, Inc., Hoboken.

Öztuna, D., & Elhan, A. H. (2006). Investigation of Four Different Normality Tests in Terms of Type 1 Error Rate and Power under Different Distributions. *Tubitak*, 171-176.

Raudenbush, & Cheong, S. (2006). *Hierarchical linear and non-linear modeling.* London: Scientific Software International, Inc.

Rencher, A., & Schaalje, B. (2007). *Linear Model in Statistics.* USA: A john Willey & sons, INC.

Robert, C., & Casella, G. (2011). A Short History of Markov Chain Monte. *Statistical Science*, 102-115.

Snijders, T., & Bosker, R. (2002). *An Introduction to Basic and advanced multilevel modeling.* London: SAGE Publication limited.

Woltman, H., Feldstain, A., & MacKay, C. (2012). An Introduction to Hierarchical Linear Modeling. *Tutorials in Quantitative Methods for Psychology*, Vol 8(1) p 52-69.

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BIOGRAPHY

The authors' name is Mashini Milimo, born in June 21, 1988 Arusha-Tanzania. His religion is Islam. My way of higher education start by graduates BA.Statistics in 2013 at University of Dar es Salaam (UDSM) Tanzania. In 2014 the author employed by Ministry of Industry and Trade as statistician position held from 2014 till now.

In August 2017, the author went to Indonesia for MSc Statistics at Institut Teknologi Sepuluh Nopember where he equipped with different knowledge from Data mining technique, Bayesian Statistics, Computational, Research methods and Data analysis Technique.

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APPENDICES

Appendix 1.Goodness of Fit

#	Distribution	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
38	Log-Logistic (3P)	0.06393	1	0.18146	3	1.747	11
37	Log-Logistic	0.06395	2	0.23061	9	1.8989	13
18	Frechet (3P)	0.06399	3	0.16776	1	1.8245	12
61	Wakeby	0.06573	4	0.19637	5	0.63801	1
25	Gen. Pareto	0.06755	5	7.82	47	N/A	
47	Pearson 5 (3P)	0.06964	6	0.17527	2	2.4943	16
46	Pearson 5	0.07158	7	0.32559	16	2.3621	14
21	Gen. Extreme Value	0.07345	8	0.23729	11	2.6717	19
36	Log-Gamma	0.07528	9	0.19015	4	1.5517	7
48	Pearson 6	0.07621	10	0.35953	18	2.3847	15
24	Gen. Logistic	0.07839	11	0.33939	17	2.5771	17
39	Log-Pearson 3	0.07982	12	0.2094	6	0.80011	2
42	Lognormal (3P)	0.08151	13	0.22238	7	1.4085	5
29	Inv. Gaussian	0.08202	14	0.22589	8	1.3663	3
41	Lognormal	0.08314	15	0.23229	10	1.4099	6
30	Inv. Gaussian (3P)	0.08637	16	0.24139	12	1.3879	4
31	Johnson SB	0.08684	17	18.479	52	N/A	
15	Fatigue Life	0.08816	18	0.27094	13	1.5739	8
23	Gen. Gamma (4P)	0.08946	19	0.30505	15	1.5805	10
17	Frechet	0.09179	20	0.65722	20	3.2042	20
49	Pearson 6 (4P)	0.09306	21	1.368	24	6.0497	25

Appendix 2. Kolmogorov Smirnov Test

Log-Logistic (3P) [#38]					
Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	59 0.06393 0.95672 1				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.13686	0.15639	0.17373	0.19427	0.20844
Reject?	No	No	No	No	No

Appendix 3. Source code Hierarchial Log logistic of two level for Modeling per capita expenditure

```
model;
{
   for( i in 1 : N ) {
      y[i] ~ dllog3p(mu[i , R[i]],tau[R[i]],lambda[R[i]])
   }
   for( j in 1 :M ) {
      lambda[j] ~ dnorm( 1,0.5)
   }
   for( j in 1 : M ) {
      b0[j] ~ dnorm(mu.b0[j],tau.b0)
   }

   for( j in 1 : M ) {
      tau[j] ~ dgamma(2,1)
   }

   for( i in 1 : N ) {
     # mu[i , R[i]] <- b0[R[i]] + b[1,R[i]] * x1[i] + b[2,R[i]] * x2[i] + b[3,R[i]] * x3[i]
    #  mu[i , R[i]] <- b0[R[i]] + b[1,R[i]] * x[i,1] + b[2,R[i]] * x[i,2] + b[3,R[i]] * x[i,3]
mu[i , R[i]] <- b0[R[i]] +inprod( b[,R[i]] , x[i,] )
   }
   for( j in 1 : M ) {

  #mu.b0[j] <- gam.g00 + gam.g00[1] * g[j,1] + gam.g00[2] * g[j,2]
  mu.b0[j] <- gam.g000 + inprod(gam.g00[] , g[j,] )

   }
```

```
 for( j in 1 : M ) {
for(k in 1:P1){
      b[k,j] ~ dnorm(mu.b[j,k],tau.b[j])
   }
   }

 tau.b0 ~ dgamma(2,1)
for(j in 1:M){
  tau.b[j] ~ dgamma(2,1)

   }
  for( j in 1 : M ) {
for (k in 1:P1){
       mu.b[j,k] <- gam.g0[j] +inprod( gam.g[,k] , g[j,])

}
   }

  gam.g000 ~ dnorm( 90,0.75)

for(l in 1:P2){
  gam.g00[l] ~ dnorm(  90,0.75)

}

   for (j in 1:M){
   gam.g0[j] ~ dnorm( 90,0.75)
 }
for(k in 1:P1){
for(l in 1:P2){
   gam.g[l,k] ~ dnorm(  90,0.75)

}
}
}

INIT
```

Appendix 4. Result of Hierarchial Log Logistic Micro Per capita Expenditure

Node	Mean	sd	MC error	2.50%	Median	97.50%
b[1,1]	-0.00761	0.01059	2.47E-04	-0.02864	-0.00753	0.0131
b[1,2]	0.003535	0.005399	6.24E-05	-0.00716	0.003541	0.01422
b[1,3]	0.008461	0.004666	5.81E-05	-0.00101	0.008576	0.01738
b[1,4]	2.95E-04	0.003739	4.35E-05	-0.00716	3.24E-04	0.007614
b[1,5]	0.006038	0.005971	1.03E-04	-0.00566	0.006044	0.01772
b[1,6]	0.01534	0.0091	2.05E-04	-0.00254	0.01517	0.03406
b[1,7]	-0.00563	0.005531	8.00E-05	-0.01668	-0.00558	0.005311
b[2,1]	-0.04425	0.1947	0.002271	-0.4211	-0.04638	0.353
b[2,2]	0.03492	0.1549	0.001179	-0.2729	0.03472	0.3389
b[2,3]	0.2554	0.1298	8.34E-04	0.001987	0.2549	0.5086
b[2,4]	-0.07239	0.09498	5.47E-04	-0.2582	-0.07322	0.1171
b[2,5]	0.1189	0.1414	0.001009	-0.1595	0.1191	0.4013
b[2,6]	0.157	0.3697	0.00878	-0.5727	0.1533	0.9035
b[2,7]	0.04339	0.1937	0.001651	-0.337	0.04241	0.4279
b[3,1]	-0.07691	0.4892	0.006248	-1.06	-0.0727	0.8857
b[3,2]	-0.638	0.3697	0.005236	-1.375	-0.6417	0.09372
b[3,3]	-0.5188	0.4094	0.007651	-1.352	-0.5094	0.2608
b[3,4]	0.4158	0.6505	0.01667	-0.8635	0.4055	1.734
b[3,5]	-0.12	0.164	0.001201	-0.4399	-0.1212	0.2043
b[3,6]	-0.8124	1.051	0.0372	-2.928	-0.7963	1.255
b[3,7]	50.48	12.37	0.9342	30.11	48.67	75.69
b[4,1]	0.1202	0.2679	0.00628	-0.4128	0.1227	0.6411
b[4,2]	0.09247	0.0876	8.03E-04	-0.07953	0.09168	0.2671
b[4,3]	0.05277	0.07678	6.47E-04	-0.09639	0.05213	0.2054
b[4,4]	0.06428	0.07278	6.38E-04	-0.08095	0.06479	0.2069
b[4,5]	0.09143	0.103	0.002073	-0.1116	0.09147	0.2952
b[4,6]	-0.201	0.2876	0.0108	-0.7996	-0.1915	0.3315
b[4,7]	0.01681	0.1153	0.001416	-0.2132	0.01684	0.2428
b[5,1]	-0.06887	0.05791	7.68E-04	-0.1819	-0.06931	0.04698
b[5,2]	-0.1181	0.05519	6.11E-04	-0.2277	-0.1183	-0.00942
b[5,3]	-0.1095	0.04471	4.10E-04	-0.1982	-0.1095	-0.02122
b[5,4]	-0.1067	0.03366	3.30E-04	-0.1732	-0.1067	-0.04117
b[5,5]	-0.1406	0.04129	3.69E-04	-0.2221	-0.1406	-0.05845
b[5,6]	-0.2099	0.07955	0.002212	-0.3721	-0.2089	-0.05494
b[5,7]	-0.1487	0.05395	5.32E-04	-0.2537	-0.1492	-0.04084
b[6,1]	48840	46570	261.5	-42410	48520	140800
b[6,2]	27100	25680	151.3	-23520	27180	77090

Node	Mean	sd	MC error	2.50%	Median	97.50%
b[6,3]	0.1687	0.3977	0.003138	-0.6198	0.1671	0.96
b[6,4]	23790	22760	135.3	-21410	23900	68890
b[6,5]	-0.0463	0.2364	0.002445	-0.5065	-0.05092	0.4241
b[6,6]	22180	21390	109.8	-2.0E+04	22130	64210
b[6,7]	17130	16450	98.66	-15210	17050	49590
b[7,1]	113.7	16.84	1.273	76.07	116.2	140.4
b[7,2]	-33.77	12.25	0.9226	-56.01	-33.42	-12.46
b[7,3]	0.308	0.3228	0.004964	-0.3346	0.3101	0.9465
b[7,4]	19.47	20.44	1.552	-10.92	15.05	65.03
b[7,5]	-0.4259	0.2547	0.002017	-0.9328	-0.4252	0.07561
b[7,6]	0.5396	1.13	0.03849	-1.695	0.5268	2.791
b[7,7]	-33.42	25.76	1.958	-80.73	-23.01	6.296
b[8,1]	113.9	16.84	1.273	76.29	116.4	140.6
b[8,2]	-33.57	12.24	0.9224	-55.79	-33.21	-12.29
b[8,3]	0.6786	0.3459	0.004718	-0.00128	0.6804	1.361
b[8,4]	19.38	20.44	1.552	-11.01	14.93	64.94
b[8,5]	-0.202	0.4195	0.004455	-1.025	-0.1978	0.6195
b[8,6]	0.1474	1.199	0.04334	-2.222	0.1461	2.51
b[8,7]	-33.92	25.77	1.958	-81.2	-23.46	5.814
b[9,1]	48700	46620	264.3	-44610	48740	141200
b[9,2]	-33.02	12.24	0.9224	-55.23	-32.68	-11.68
b[9,3]	-0.07219	0.6643	0.007324	-1.388	-0.07199	1.241
b[9,4]	23790	22730	136.6	-21340	23920	68410
b[9,5]	383.1	98.93	7.486	205.6	370	552.9
b[9,6]	1.62	1.589	0.0534	-1.507	1.61	4.809
b[9,7]	-33.48	25.76	1.958	-80.76	-23.04	6.228
b[10,1]	48920	46270	249.9	-42550	49310	140300
b[10,2]	27160	26080	154.9	-24060	27090	78950
b[10,3]	0.6218	0.4047	0.005407	-0.1838	0.6248	1.424
b[10,4]	-264.3	46.14	3.448	-364	-260.3	-171.3
b[10,5]	0.1971	0.3989	0.004659	-0.5934	0.1967	0.9856
b[10,6]	-0.00555	1.748	0.0599	-3.485	-0.01225	3.456
b[10,7]	-33.02	25.76	1.958	-80.26	-22.55	6.71
b[11,1]	113.9	16.85	1.274	76.31	116.3	140.7
b[11,2]	-33.19	12.24	0.9226	-55.41	-32.85	-11.88
b[11,3]	1.038	0.5785	0.003827	-0.1097	1.035	2.193
b[11,4]	19.6	20.44	1.552	-10.77	15.13	65.16
b[11,5]	-0.2577	0.2648	0.002406	-0.7817	-0.258	0.2586
b[11,6]	1.788	1.439	0.04809	-1.052	1.761	4.708

Node	Mean	sd	MC error	2.50%	Median	97.50%
b[11,7]	-32.99	25.76	1.958	-80.26	-22.54	6.732
b[12,1]	1.554	29.81	2.265	-38.15	-8.207	64.69
b[12,2]	27100	25880	155.4	-23500	26830	78430
b[12,3]	29980	28840	182.6	-27260	30070	86450
b[12,4]	28.86	12.94	0.9792	3.927	29.63	50.66
b[12,5]	-0.2355	0.6769	0.005575	-1.598	-0.2301	1.08
b[12,6]	22330	21400	105.6	-19690	22430	64360
b[12,7]	-99.75	25.87	1.965	-145.8	-96.85	-44.54
b[13,1]	-621.6	81.93	6.185	-759.9	-628.2	-463
b[13,2]	-23.07	11.12	0.8331	-42.81	-23.96	-2.522
b[13,3]	-47.53	21.25	1.613	-89.18	-45.43	-12.58
b[13,4]	23690	22540	129	-20770	23740	68050
b[13,5]	0.003868	0.5364	0.006788	-1.034	-4.67E-4	1.07
b[13,6]	-2.697	1.836	0.06794	-6.472	-2.681	0.8972
b[13,7]	16970	16310	102	-15100	16970	49320
b[14,1]	1.46	29.81	2.265	-38.23	-8.394	64.41
b[14,2]	9.043	11.44	0.8605	-14.1	9.116	31.95
b[14,3]	-47.22	21.22	1.612	-88.83	-45.09	-12.23
b[14,4]	23800	22710	143.3	-21090	23810	68330
b[14,5]	-0.07054	0.3147	0.004954	-0.6996	-0.06922	0.5423
b[14,6]	-1.923	1.27	0.05103	-4.503	-1.917	0.5686
b[14,7]	-99.42	25.88	1.966	-145.5	-96.47	-44.2
b[15,1]	1.489	29.81	2.266	-38.22	-8.399	64.54
b[15,2]	9.657	11.44	0.8609	-13.44	9.683	32.61
b[15,3]	-47.83	21.22	1.612	-89.46	-45.7	-12.81
b[15,4]	29.86	12.93	0.9792	4.94	30.61	51.59
b[15,5]	-0.2519	0.3514	0.004322	-0.9547	-0.2479	0.4352
b[15,6]	-1.202	1.036	0.04023	-3.308	-1.191	0.8281
b[15,7]	-99.8	25.87	1.965	-145.9	-96.85	-44.55
b[16,1]	0.1682	0.4503	0.006177	-0.7247	0.1683	1.065
b[16,2]	-2.077	0.7014	0.01612	-3.459	-2.076	-0.6935
b[16,3]	0.4297	0.364	0.004134	-0.3078	0.4345	1.133
b[16,4]	-0.6213	0.479	0.01112	-1.591	-0.6143	0.3286
b[16,5]	-0.04806	0.2917	0.002645	-0.6403	-0.04146	0.508
b[16,6]	0.09003	0.4697	0.01089	-0.8439	0.09115	1.028
b[16,7]	126.4	19.6	1.486	79.73	123.5	157.7
b[17,1]	0.7266	0.6744	0.009066	-0.6069	0.722	2.06
b[17,2]	-1.953	0.7639	0.01752	-3.471	-1.954	-0.4411
b[17,3]	0.946	0.4043	0.004297	0.1493	0.9475	1.747

Node	Mean	sd	MC error	2.50%	Median	97.50%
b[17,4]	283.1	57.55	4.328	182.8	274	420.8
b[17,5]	-0.2982	0.2973	0.003673	-0.8999	-0.2936	0.2777
b[17,6]	-0.3306	0.745	0.02127	-1.783	-0.3466	1.19
b[17,7]	126	19.61	1.487	79.48	123.2	157.5
b[18,1]	48820	46460	283.6	-43180	48520	140800
b[18,2]	-1.86	0.98	0.01955	-3.785	-1.866	0.07009
b[18,3]	0.3078	0.4192	0.003838	-0.547	0.3142	1.123
b[18,4]	-0.5808	0.559	0.01186	-1.701	-0.5785	0.5191
b[18,5]	-383.7	98.93	7.485	-553.7	-370.6	-206.2
b[18,6]	-1.363	1.198	0.03476	-3.789	-1.365	1.028
b[18,7]	126.6	19.6	1.486	79.85	123.7	158
b[19,1]	0.1644	0.4622	0.006536	-0.754	0.1676	1.066
b[19,2]	-1.949	0.7106	0.01668	-3.351	-1.945	-0.526
b[19,3]	0.2835	0.3109	0.003456	-0.3512	0.2869	0.885
b[19,4]	-0.6231	0.4868	0.01164	-1.61	-0.6154	0.3411
b[19,5]	-0.2705	0.4044	0.004069	-1.077	-0.2648	0.505
b[19,6]	-0.1233	0.4383	0.01041	-0.991	-0.1287	0.7667
b[19,7]	126.4	19.6	1.487	79.78	123.6	157.8
b[20,1]	-0.2591	0.2647	0.00373	-0.7902	-0.2575	0.2613
b[20,2]	0.1251	0.1914	0.00146	-0.2549	0.1253	0.5007
b[20,3]	-0.06264	0.1979	0.001781	-0.4524	-0.06255	0.3315
b[20,4]	0.05767	0.1364	0.001151	-0.2117	0.05736	0.3282
b[20,5]	0.2843	0.162	0.00135	-0.0311	0.2832	0.6046
b[20,6]	0.3117	0.4725	0.01557	-0.6261	0.3124	1.259
b[20,7]	0.2445	0.1824	0.001292	-0.1237	0.2461	0.6024
b[21,1]	623.9	87.97	6.652	460.1	636.2	761.4
b[21,2]	26850	26140	173.2	-24290	26800	78610
b[21,3]	0.6316	0.3404	0.003209	-0.0326	0.6287	1.301
b[21,4]	23770	22620	138.4	-20790	23700	68390
b[21,5]	-0.06994	0.2104	0.001376	-0.4838	-0.07175	0.3477
b[21,6]	1.955	0.7255	0.02141	0.5231	1.948	3.432
b[21,7]	17280	16300	96.9	-14930	17160	49730
b[22,1]	-0.1922	0.2707	0.003107	-0.7347	-0.1933	0.3431
b[22,2]	0.07552	0.1865	0.001795	-0.2904	0.07435	0.4465
b[22,3]	-0.1792	0.1999	0.001768	-0.5744	-0.1784	0.2135
b[22,4]	0.07306	0.1457	9.07E-04	-0.2137	0.0727	0.3626
b[22,5]	0.02625	0.2006	0.001548	-0.379	0.02891	0.4145
b[22,6]	0.06657	0.4391	0.0105	-0.8105	0.06443	0.958
b[22,7]	-0.09414	0.1702	0.001435	-0.4294	-0.09527	0.2437

Node	Mean	sd	MC error	2.50%	Median	97.50%
b[23,1]	48880	46720	272.8	-44820	49050	140400
b[23,2]	-0.6432	0.7684	0.01199	-2.153	-0.6416	0.8987
b[23,3]	0.4356	0.4829	0.005027	-0.5155	0.4376	1.386
b[23,4]	0.6438	0.457	0.002691	-0.2707	0.6474	1.551
b[23,5]	0.1548	0.2649	0.002451	-0.3754	0.1585	0.6679
b[23,6]	1.586	0.7855	0.02286	0.05239	1.571	3.194
b[23,7]	16960	16420	91.72	-15340	16890	49390
b[24,1]	0.2756	0.3072	0.002563	-0.3285	0.2716	0.8941
b[24,2]	0.1786	0.1831	0.001883	-0.1828	0.1788	0.5411
b[24,3]	-0.00547	0.1735	0.001247	-0.3482	-0.00654	0.3438
b[24,4]	0.3474	0.1877	0.001037	-0.0231	0.3477	0.7176
b[24,5]	0.2459	0.1733	0.00121	-0.09752	0.2465	0.5874
b[24,6]	0.8388	0.4561	0.01524	-0.02648	0.8231	1.786
b[24,7]	0.2179	0.2802	0.00197	-0.3413	0.2189	0.7756
b[25,1]	48990	46600	286.8	-43140	48800	141300
b[25,2]	27020	25860	158.9	-24660	27180	77890
b[25,3]	0.3559	0.4249	0.00475	-0.4836	0.356	1.198
b[25,4]	23460	22570	121.1	-21140	23560	68140
b[25,5]	0.4016	0.2344	0.001776	-0.0595	0.4012	0.8672
b[25,6]	-2.861	1.261	0.04066	-5.405	-2.85	-0.3795
b[25,7]	1.70E+04	16340	99.48	-15130	17100	49200
b[26,1]	0.2207	0.2989	0.00342	-0.37	0.2195	0.8092
b[26,2]	0.1698	0.1702	0.001278	-0.1676	0.1697	0.5058
b[26,3]	0.1126	0.1791	0.001433	-0.2413	0.1143	0.4594
b[26,4]	0.2172	0.1884	0.00159	-0.1533	0.2174	0.5867
b[26,5]	-0.1536	0.1973	0.001728	-0.5368	-0.1549	0.2353
b[26,6]	-0.2464	0.4813	0.01073	-1.231	-0.2386	0.7002
b[26,7]	0.2173	0.2122	0.00175	-0.1986	0.2169	0.6412
b[27,1]	0.1035	0.3171	0.00239	-0.5444	0.1113	0.7231
b[27,2]	0.2603	0.2318	0.002568	-0.1929	0.2592	0.7184
b[27,3]	0.6849	0.1958	0.001317	0.2958	0.687	1.068
b[27,4]	0.4578	0.1621	0.001122	0.1373	0.4582	0.7797
b[27,5]	-0.129	0.3271	0.002168	-0.797	-0.1234	0.4955
b[27,6]	0.1439	0.2905	0.005018	-0.4268	0.1434	0.7265
b[27,7]	-0.1166	0.4718	0.003005	-1.041	-0.1174	0.8248

Appendix 5. Result of Hierarchial Log Logistic Macro Per Capita Expenditure

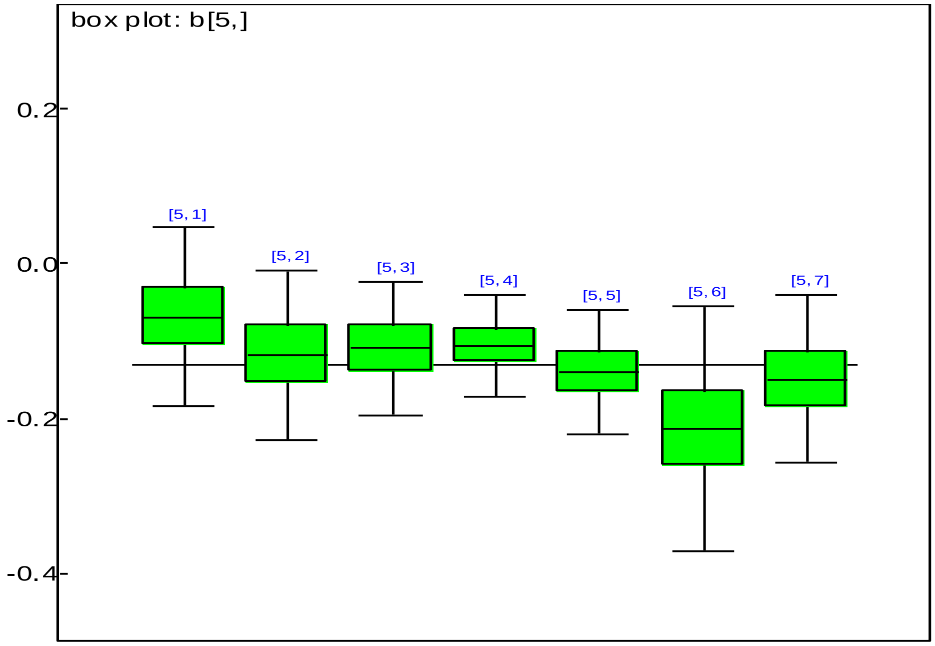
Node	Mean	sd	MC error	2.50%	Meadian	97.50%
gam.g[1,1]	89.97	1.16	0.006807	87.71	89.97	92.26
gam.g[1,2]	89.99	1.146	0.006369	87.74	89.99	92.24
gam.g[1,3]	89.98	1.153	0.006399	87.71	89.98	92.22
gam.g[1,4]	89.98	1.155	0.006465	87.71	89.97	92.21
gam.g[1,5]	89.99	1.157	0.006672	87.73	90	92.24
gam.g[1,6]	90	1.149	0.006824	87.78	90	92.26
gam.g[1,7]	89.96	1.153	0.006374	87.69	89.96	92.22
gam.g[1,8]	89.99	1.148	0.006538	87.73	89.98	92.23
gam.g[1,9]	89.98	1.152	0.006299	87.7	89.98	92.23
gam.g[1,10]	89.99	1.15	0.006771	87.73	90	92.23
gam.g[1,11]	89.98	1.156	0.007345	87.71	89.98	92.25
gam.g[1,12]	89.99	1.152	0.006654	87.72	89.98	92.24
gam.g[1,13]	89.98	1.148	0.006731	87.73	89.98	92.23
gam.g[1,14]	89.99	1.158	0.007176	87.71	89.99	92.25
gam.g[1,15]	89.97	1.154	0.00678	87.74	89.97	92.25
gam.g[1,16]	89.98	1.167	0.006049	87.69	89.99	92.25
gam.g[1,17]	89.98	1.15	0.007113	87.7	89.98	92.22
gam.g[1,18]	89.98	1.157	0.006462	87.73	89.98	92.26
gam.g[1,19]	89.98	1.158	0.007065	87.72	89.98	92.24
gam.g[1,20]	89.98	1.16	0.006308	87.7	89.97	92.26
gam.g[1,21]	89.98	1.158	0.006838	87.71	89.99	92.25
gam.g[1,22]	89.98	1.149	0.006284	87.76	89.98	92.24
gam.g[1,23]	89.98	1.16	0.006674	87.71	89.98	92.26
gam.g[1,24]	89.97	1.153	0.006248	87.72	89.98	92.24
gam.g[1,25]	90	1.157	0.007024	87.7	90	92.29
gam.g[1,26]	89.98	1.157	0.007121	87.7	89.98	92.24
gam.g[1,27]	89.98	1.151	0.006468	87.71	89.98	92.23
gam.g[2,1]	89.99	1.155	0.00659	87.74	89.99	92.25
gam.g[2,2]	90	1.155	0.006865	87.74	90	92.26
gam.g[2,3]	89.99	1.155	0.006721	87.73	90	92.27
gam.g[2,4]	89.99	1.152	0.006221	87.71	89.99	92.25
gam.g[2,5]	89.98	1.15	0.006699	87.72	89.98	92.23
gam.g[2,6]	90	1.157	0.006641	87.74	90	92.27
gam.g[2,7]	89.98	1.155	0.005983	87.71	89.98	92.26
gam.g[2,8]	89.99	1.149	0.006576	87.75	89.98	92.24
Node	Mean	sd	MC error	2.50%	Meadian	97.50%
gam.g[2,9]	89.99	1.149	0.007159	87.74	89.99	92.24

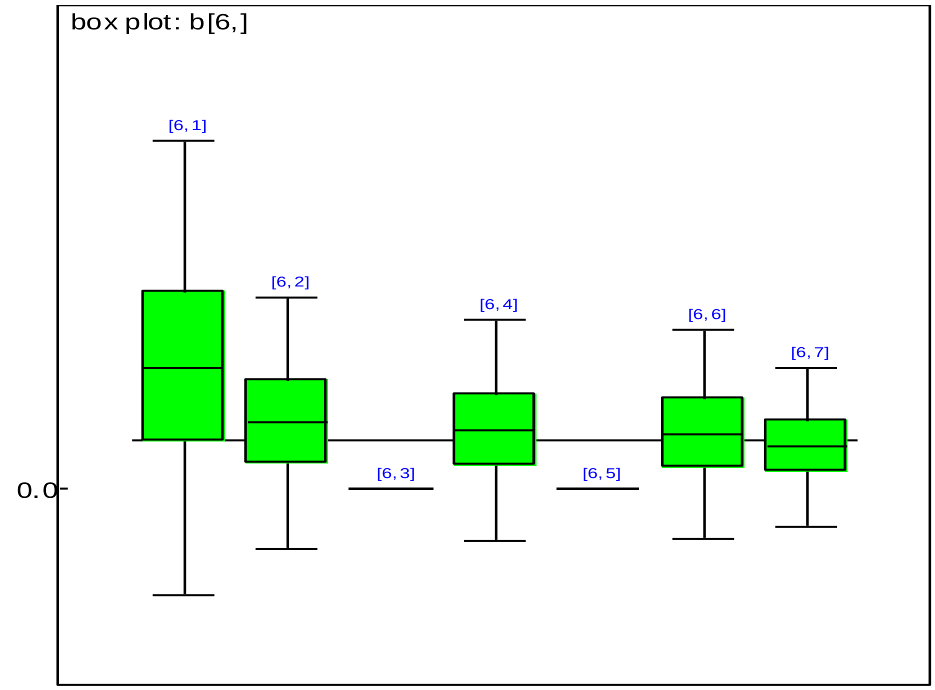
gam.g[2,10]	90	1.159	0.006606	87.73	90	92.27
gam.g[2,11]	89.99	1.157	0.006731	87.73	89.99	92.27
gam.g[2,12]	90.01	1.153	0.006785	87.73	90	92.25
gam.g[2,13]	89.99	1.146	0.006581	87.73	89.99	92.24
gam.g[2,14]	89.99	1.153	0.007095	87.72	89.99	92.24
gam.g[2,15]	89.99	1.153	0.006735	87.76	89.99	92.26
gam.g[2,16]	90	1.147	0.007027	87.74	90.01	92.23
gam.g[2,17]	90	1.151	0.006543	87.75	90	92.24
gam.g[2,18]	90.01	1.158	0.006466	87.72	90.01	92.27
gam.g[2,19]	89.99	1.161	0.006348	87.71	90	92.27
gam.g[2,20]	90	1.158	0.006798	87.75	90	92.27
gam.g[2,21]	89.99	1.162	0.006713	87.69	89.99	92.25
gam.g[2,22]	89.99	1.156	0.006196	87.73	89.99	92.27
gam.g[2,23]	89.99	1.153	0.007022	87.71	89.99	92.27
gam.g[2,24]	90	1.155	0.006792	87.73	90	92.25
gam.g[2,25]	90	1.147	0.006835	87.74	90	92.25
gam.g[2,26]	89.99	1.146	0.006269	87.74	89.99	92.25
gam.g[2,27]	89.99	1.151	0.006407	87.75	89.99	92.24
gam.g[3,1]	89.94	1.158	0.007096	87.68	89.94	92.23
gam.g[3,2]	89.93	1.161	0.005785	87.66	89.94	92.2
gam.g[3,3]	89.96	1.157	0.006297	87.69	89.96	92.23
gam.g[3,4]	89.95	1.155	0.0073	87.7	89.95	92.22
gam.g[3,5]	89.95	1.156	0.006382	87.69	89.96	92.22
gam.g[3,6]	89.98	1.151	0.006602	87.72	89.98	92.26
gam.g[3,7]	89.95	1.158	0.006681	87.69	89.95	92.2
gam.g[3,8]	89.95	1.148	0.006031	87.71	89.95	92.21
gam.g[3,9]	89.97	1.152	0.006922	87.75	89.97	92.24
gam.g[3,10]	89.97	1.152	0.007061	87.72	89.97	92.24
gam.g[3,11]	89.94	1.159	0.00688	87.66	89.94	92.23
gam.g[3,12]	89.96	1.16	0.006604	87.71	89.95	92.23
gam.g[3,13]	89.96	1.159	0.0067	87.67	89.96	92.25
gam.g[3,14]	89.94	1.148	0.006665	87.71	89.93	92.18
gam.g[3,15]	89.94	1.144	0.006774	87.7	89.94	92.19
gam.g[3,16]	89.95	1.153	0.005807	87.69	89.96	92.19
gam.g[3,17]	89.94	1.157	0.006777	87.65	89.95	92.19
gam.g[3,18]	89.97	1.157	0.006534	87.69	89.97	92.25
gam.g[3,19]	89.95	1.152	0.007037	87.67	89.94	92.19
gam.g[3,20]	89.95	1.153	0.006496	87.71	89.95	92.22
Node	Mean	sd	MC error	2.50%	Meadian	97.50%
gam.g[3,21]	89.96	1.162	0.006274	87.68	89.95	92.23

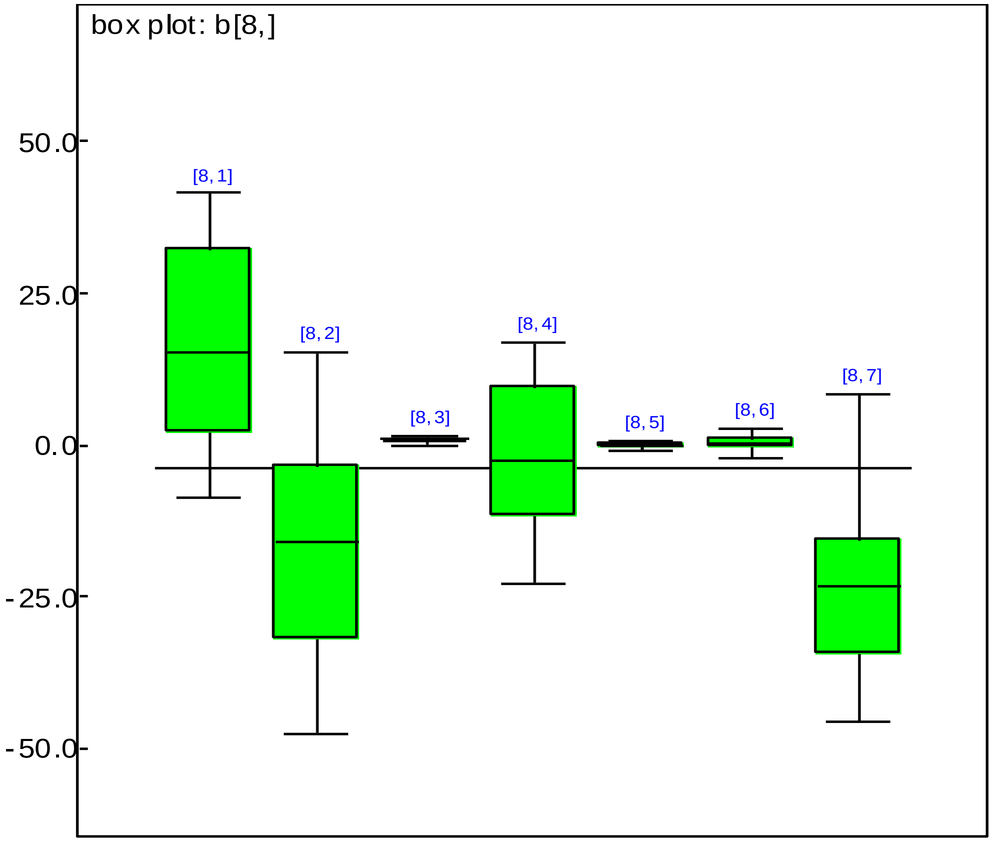
gam.g[3,22]	89.95	1.146	0.006684	87.72	89.95	92.19
gam.g[3,23]	89.97	1.153	0.006484	87.72	89.97	92.25
gam.g[3,24]	89.95	1.159	0.006897	87.66	89.95	92.2
gam.g[3,25]	90	1.149	0.006213	87.75	90.01	92.26
gam.g[3,26]	89.94	1.154	0.006534	87.68	89.94	92.22
gam.g[3,27]	89.94	1.152	0.006466	87.66	89.94	92.19
gam.g[4,1]	89.96	1.16	0.005967	87.71	89.96	92.26
gam.g[4,2]	89.94	1.159	0.006878	87.68	89.94	92.22
gam.g[4,3]	89.96	1.153	0.0071	87.71	89.96	92.25
gam.g[4,4]	89.97	1.156	0.006401	87.71	89.97	92.23
gam.g[4,5]	89.96	1.156	0.007613	87.68	89.97	92.24
gam.g[4,6]	89.98	1.157	0.006687	87.72	89.98	92.24
gam.g[4,7]	89.97	1.156	0.006476	87.71	89.97	92.25
gam.g[4,8]	89.96	1.156	0.006412	87.69	89.97	92.21
gam.g[4,9]	89.97	1.146	0.006923	87.71	89.97	92.23
gam.g[4,10]	89.96	1.153	0.00605	87.71	89.96	92.2
gam.g[4,11]	89.97	1.156	0.007206	87.72	89.96	92.25
gam.g[4,12]	89.98	1.159	0.005933	87.68	89.99	92.23
gam.g[4,13]	89.97	1.157	0.007286	87.68	89.97	92.24
gam.g[4,14]	89.97	1.153	0.006446	87.71	89.97	92.23
gam.g[4,15]	89.96	1.162	0.006565	87.67	89.96	92.23
gam.g[4,16]	89.96	1.152	0.005694	87.7	89.96	92.22
gam.g[4,17]	89.95	1.155	0.006983	87.7	89.94	92.22
gam.g[4,18]	89.96	1.156	0.007035	87.69	89.96	92.23
gam.g[4,19]	89.97	1.152	0.006703	87.7	89.97	92.22
gam.g[4,20]	89.97	1.158	0.006629	87.71	89.97	92.24
gam.g[4,21]	89.97	1.162	0.00658	87.7	89.98	92.24
gam.g[4,22]	89.97	1.154	0.007121	87.72	89.97	92.22
gam.g[4,23]	89.96	1.15	0.00661	87.71	89.95	92.22
gam.g[4,24]	89.95	1.161	0.006652	87.68	89.95	92.22
gam.g[4,25]	89.98	1.154	0.006715	87.72	89.97	92.24
gam.g[4,26]	89.95	1.144	0.006367	87.7	89.96	92.2
gam.g[4,27]	89.95	1.152	0.006535	87.7	89.94	92.21
gam.g0[1]	90.02	1.149	0.007116	87.76	90.02	92.26
gam.g0[2]	90	1.149	0.006345	87.73	90	92.25
gam.g0[3]	90	1.157	0.006617	87.72	89.99	92.28
gam.g0[4]	89.99	1.155	0.006579	87.75	89.98	92.25
gam.g0[5]	90	1.158	0.006667	87.74	90.01	92.28
Node	Mean	sd	MC error	2.50%	Meadian	97.50%
gam.g0[6]	90	1.163	0.007288	87.74	90	92.29

gam.g0[7]	90	1.154	0.007517	87.74	89.99	92.28
gam.g00[1]	89.98	1.151	0.006114	87.71	89.98	92.21
gam.g00[2]	89.99	1.156	0.006575	87.72	89.99	92.27
gam.g00[3]	89.93	1.152	0.006101	87.68	89.93	92.19
gam.g00[4]	89.95	1.159	0.006394	87.67	89.95	92.23
gam.g000	89.99	1.16	0.007248	87.75	89.98	92.29
lambda[1]	0.9922	1.419	0.008254	-1.77	0.9846	3.762
lambda[2]	1.014	1.41	0.008439	-1.753	1.014	3.777
lambda[3]	0.9961	1.419	0.007768	-1.782	0.9949	3.799
lambda[4]	1.008	1.412	0.007575	-1.744	1.012	3.771
lambda[5]	0.9899	1.405	0.008894	-1.772	0.999	3.722
lambda[6]	1.01	1.42	0.008263	-1.759	0.9948	3.787
lambda[7]	0.9948	1.41	0.008332	-1.743	0.9928	3.78
tau[1]	4.028	0.7476	0.005742	2.68	3.99	5.593
tau[2]	4.324	0.6598	0.00414	3.108	4.292	5.695
tau[3]	4.153	0.5631	0.00371	3.115	4.133	5.318
tau[4]	5.002	0.7412	0.005061	3.65	4.973	6.542
tau[5]	4	0.482	0.003496	3.095	3.988	4.985
tau[6]	4.47	1.093	0.01534	2.557	4.401	6.8
tau[7]	5.18	0.9804	0.006419	3.402	5.124	7.245
tau.b[1]	5.04E-10	1.75E-10	9.47E-13	2.60E-1(	4.92E-1(	8.22E-1
tau.b[2]	1.61E-09	4.58E-10	2.74E-12	8.52E-1(	1.57E-0(	2.59E-0
tau.b[3]	1.29E-09	3.53E-10	2.04E-12	7.21E-1(	1.26E-0(	2.04E-0
tau.b[4]	2.11E-09	6.07E-10	3.35E-12	1.11E-0(	2.05E-0(	3.43E-0
tau.b[5]	3.10E-10	1.27E-10	7.04E-13	1.76E-1(	3.03E-1(	4.80E-1
tau.b[6]	2.35E-09	6.25E-10	3.53E-12	1.30E-0(	2.30E-0(	3.72E-0
tau.b[7]	4.05E-09	1.13E-0(	6.45E-12	2.15E-0(	3.94E-0(	6.49E-0
tau.b0	1.22E-09	5.29E-10	2.83E-12	4.24E-1(	1.14E-0(	2.44E-0

Appendix 6. Box Plot Micro Regression Coeffients Alternative 1






box plot: b[8,]
50.0
25.0
0.0
-25.0
-50.0
[8, 1]
[8, 2]
[8, 3]
[8, 4]
[8, 5]
[8, 6]
[8, 7]