# MIXTURE OF GAMMA REGRESSION ON MATERNITY LENGTH OF STAY

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Abstract: In literature one of the risk factors for maternity length of stay (MLOS) is age. Women are mostly fertile at age less than 25 years and it greatly reduced thereafter with associated complications. The population of the study comprises of 701 pregnant women that visited 4 hospitals in Funtua, Katsina State, Nigeria for childbirth. We considered hospital type, educational qualification, occupation, number of procedures, number of diagnosis, mode of delivery, parity, location, mother's weight and child's weight as risk factors for MLOS and proposed a mixture of gamma regression model to unearth the heterogeneous in MLOS data for two age groups of women: age less than 25 years and 25 years and above. The expectation maximization (EM) algorithm was used to estimate the model parameters and employed posterior probability for classification of objects into components. The results of the analysis show existence of two components in each of the two groups corresponding to short-stay patient and long-stay patient components. The proportions of patients in short-stay and long-stay components are 0.79 and 0.21 with average length of stay 1.34 days and 5.36 days, respectively for women in age group less the 25 years. Similar trend is observed in age group 25 years and above. There are 9 risk factors (hospital type, location, educational qualification, model of delivery, mother weight, baby weight and number of procedures,) that affect long-stay compare to four factors (educational qualification, model of delivery and number of procedures) that affect short-stay in age group 25 years and above. Only four factors (hospital type, educational qualification, model of delivery and mother weight) affect the short-stay and long-stay in the other group (ageless 25 years). Therefore, more resource allocations will be needed in terms of intervention for older pregnant women.

**Keywords:** Mixture model, Age, length of stay, EM algorithms, maternity, complications

## Introduction

Length of stay (LOS) is a term commonly used to measure duration of a particular occurrence of hospitalization. Patient days are calculated by subtracting day of admission from day of discharge. People entering and leaving a hospital on the same day have a LOS of one. Patient length of stay (LOS) is one of the most commonly employed outcome measures for hospital resource consumption and performance monitoring globally. Most of the hospitals around the world use average length of stay as starting point for resource planning. It also provides a better understanding of the flow of patients through a healthcare system which is essential for understanding both the operational and clinical functions of such a system (Adeyemi and Chaussalet, 2009). Maternity length of stay could be described as the numbers of days the pregnant women stayed before, during and after the child birth in the hospital. Length of stay after delivery at a health facility varies among nursing mothers (Campbell *et al.*, 2016). Some pregnant mothers spend either shorter time or longer time compared with the actual needs. LOS estimations has countless applications such as: assessing future bed usage, estimating forthcoming demands on various hospital resources, helping to understand the cause of the patient disease and recovery, explaining health insurance plans and return systems in the private sector, planning discharges for elderly patients, dependent patients or any patient with special needs and as a crucial variable for the quality of life of the patients and families (Ramakrishnan, 2012). Delivery of nursing mothers in health facilities varies as a result peculiar and general health conditions which further determine the numbers of days the nursing mother will stay in the hospital after delivery. Plough *et al.* (2017) stated that LOS in a shorter period of time leads to insufficient time for physicians to detect, to diagnose or treat complications of delivery that will in-turn increase the possibility of morbidity and mortality. Therefore, the importance of getting accurate estimation of Maternity Length of Stay (MLOS) is a crucial factor in health care management.

Lee *et al.*, (2007) proposed a two component mixture model of the gamma distribution on maternity length of stay but in their work they considered age as a factor without recourse for age classification. Wang *et al.* (2002) used two- component of a hierarchical Poisson mixture regression model to analyze maternity length of stay identifying age as a contributing factor but do not considered classifying the age. Lee *et al.* (2002) conducted research on public versus private hospital maternity length of stay using a gamma mixture modelling approach, also identified age as a contributing factor but did not considered classifying the age.

Age is considered as one of the factors affecting MLOS but it has been pointed out that a lot of changes occur to women at different ages during pregnancy. For instance, women are most fertile and have the best chance of getting pregnant in their 20s when they are naturally provided with highest number of good quality eggs and the risks of pregnancy is at the lowest. When a woman attains the age of 25 years, her odds of conceiving after 3 months of trying is under 20 percent. The fertility declines gradually around the age of 32 and after age 35 years the decline speeds up. The risks of miscarriage and genetic abnormalities also begin to rise at age 35 years. Therefore, complications set in (Wilson, 2018). The effect of this complication is for women to spend additional day(s) in the hospital. The findings of Wilson (2018) justified a critical diagnosis of length of stay of pregnant women in term of age category. It will enable researches to determine factors mostly affecting the category of these women and give opportunity for interventions. In addition, the patient's general health status and severity of disease play a major role in both the treatment selection and prognosis (Delong *et al.,* 2005). These motivated this research to split age of patients into two groups to model the maternity length of stay. The first group consists of women of age less than 25 years and the second group are those 25 years and above based on the finding of Wilson, 2018. The mixture of regression is fitted to each group.

**Materials and Methods**

The population of the study comprises of 701 pregnant women that visited 4 hospitals in Funtua, Katsina State, Nigeria for childbirth for a period of 3 years (2017 – 2019). The breakdown of this population consists of 299 registered pregnant women at private hospital and 402 from public hospital. The variables obtained from the records of the hospitals on the pregnant women are length of stay of pregnant women after delivery, age of mother, educational qualification, occupation, number of procedure (Total number of surgical procedures that patients underwent during their stay), number of diagnosis (Total number of diagnosed medical conditions), mode of delivery (normal or vaginal delivery and cesarean), parity, mother's weight, and child's weight. The data on length of stay has been reported to be positively skewed. So mixture analysis can be used to determine existence of heterogeneous subpopulations in the data (Lee *et al*., 1998).

***Finite Mixture Model***

A finite mixture model of k components in proportions $\pi_1$ ,…, $\pi_k$ , is defined as the density of $j^{th}$ response variable $Y_i$ given by:

$$f(y_i;\psi)=\sum_{j=1}^{k}\pi_j f(y_i;\gamma_j) \quad (1)$$

$0 \le \pi_j \le 1$ and $\sum_{j=1}^{k}\pi_j = 1$ and $\psi=(\pi_1,\ldots\ldots,\pi_k;\gamma_j)$.

The $\pi_j$ is the proportions of patients in $j^{th}$ component and $f(y_i;\gamma_j)$ is the $j^{th}$ component probability density with parameter $\gamma_j$. In this formulation the number of components is fixed but unknown and has to be estimated from available data, along with the mixing proportions, $\pi_j$, and component parameter(s). Then one needs to specify the component density which should be based on distributional properties of the variable of interest, MLOS. In this study we adopted gamma density which is given by:

$$f(y_i;\gamma_j)=\frac{\left(\frac{\mu_j}{\sigma_j^2}\right)^{\frac{\mu_j^2}{\sigma_j^2}} y_i^{\left(\frac{\mu_j^2}{\sigma_j^2}-1\right)}\exp\left(-\frac{\mu_j y_i}{\sigma_j^2}\right)}{\Gamma\left(\frac{\mu_j^2}{\sigma_j^2}\right)}$$

i=1… n, j=1,….,k (2)

If equation (2) is used in equation (1), then resorting to equation (3) which is referred to as mixture of gamma density with k number of components in the data. The parameters ( $\psi$ ) of the model are unknown but has to be estimated from the data.

$$f(y_i,\psi)=\pi_1\frac{\left(\frac{\mu_1}{\sigma_1^2}\right)^{\mu_1^2/\sigma_1^2} y_i^{\left(\mu_1^2/\sigma_1^2-1\right)}\exp\left(-\mu_1 y_i/\sigma_1^2\right)}{\Gamma\left(\frac{\mu_1^2}{\sigma_1^2}\right)} +\pi_2\frac{\left(\frac{\mu_2}{\sigma_2^2}\right)^{\mu_2^2/\sigma_2^2} y_i^{\left(\mu_2^2/\sigma_2^2-1\right)}\exp\left(-\mu_2 y_i/\sigma_2^2\right)}{\Gamma\left(\frac{\mu_2^2}{\sigma_2^2}\right)} +\cdots+\pi_k\frac{\left(\frac{\mu_k}{\sigma_k^2}\right)^{\mu_k^2/\sigma_k^2} y_i^{\left(\mu_k^2/\sigma_k^2-1\right)}\exp\left(-\mu_k y_i/\sigma_k^2\right)}{\Gamma\left(\frac{\mu_k^2}{\sigma_k^2}\right)} \quad (3)$$

***Parameter Estimation***

The parameters of the mixture of gamma model $\psi$ =( $\pi_j$ , $\gamma_j$ )where $\gamma_j$ =( $\mu_j$ , $\sigma_j$ ), j=1,………,k are estimated by means of maximum likelihood estimation via EM algorithm of Dempster *et al* (1977). The procedure for estimating the parameters are as follows:

Let $Y_i$ be observed data with a corresponding component-label vector $Z_j$ of zero-one indicator variable for the component in the mixture model where $Y_i$ is assumed to have arisen. In the EM setting, $y_i$ which are the realization of $Y_i$ are viewed to be incomplete since the realized values of $z_i$ are not available. The complete data is denoted by vector y $=(y', z')'$. Therefore $Z_{ij}$ = {0,1} denotes the value of $Z_j$ for observation $y_i$.

Thus, the likelihood function for the complete data is

$$L_c(\psi)=\prod_{i=1}^{n}\prod_{j=1}^{k}\pi_j^{z_{ij}} f\left(y_i;\gamma_j\right)^{z_{ij}} \quad (4)$$

The log-likelihood function of the mixture model is given by;

LogL $_c$ $(\psi)=\sum_{i=1}^{n}\sum_{j=1}^{k} z_{ij}\left\{\log\pi_j+\log f\left(y_i;\gamma_j\right)\right\}$ where (i=1,……,n; j=1,…..,k) (5)

The E – step calculates function Q( $\psi;\psi^{(t)}$ ) = $E_{\psi^{(t)}}\left\{L_c(\psi)\mid \underline{y}\right\}$

$$=\sum\sum\tau_{ij}^{(t)}\log\pi_j f\left(y_i;\gamma_j\right)$$

**where** $\tau_{ij}^{(t)}=\dfrac{\pi_j^{(t)} f(y_i;\gamma_j^{(t)})}{\sum\pi_h^{(t)} f_h(y_i;\gamma_j^{(t)})}$ is the posterior probability that the $i^{th}$ member of the sample with observed value $y_i$ belongs to the jth component at iteration t ;

The M – step is obtained by choosing $\psi^{t+1}$ = $Arg\max\{Q(\psi;\psi^{(t)}\}$

These two steps, expectation and maximization, are repeated alternatively until the difference $|\psi^{(t+1)} - \psi^{(t)}|$ changes by small quantity (McLachlan and Peel, 2000; Lee, Xiao, Codde and Ng, 2002).

### *Mixture of Gamma Regression*

The relationship between MLOS and its associated risk factors are modeled by mixture of gamma regression. Then equation (3) is now having the parameter $\gamma_j = (\mu_j, \sigma_j)$, where the $\mu_j$ >0 and $\sigma_j$ >0 are the component mean and standard deviation respectively. The mixture of gamma regression is a special case of mixture of generalized linear models (Jansen, 1993, Wedel and Desarbo, 1995). Then the log( $\mu_j$ ) in jth component are linear functions of the risk factors and are given by:

Log( $\mu_j$ ) = $\underline{x}_i^{/}\underline{\beta}_l$ ,

i= 1,2,….,n, l=1,…,d

The mixture of gamma regression is given as in term of regression, the proportion of patients belonging to the $j^{th}$ component $\pi_j$ may be expressed in terms of a set of risk variables $x_i = (x_{i1}, \ldots, x_{ip})$ of the $i^{th}$ individual through logistic transform, so that:

$$\pi_j(x_i) = \frac{\exp\left(\sum_{l=0}^{d} \delta_{jl} x_{il}\right)}{1 + \sum_{h=1}^{k-1} \exp\left(\sum_{l=0}^{d} \delta_{hl} x_{il}\right)}$$

**Where** $x_{i0} = 1$ for all $i$ , $\gamma_j = (\mu_j, \sigma_j^2)$ and $\delta_{jl} = (\delta_{j0}, \cdots, \delta_{jd})$ denotes a $(d+1)\times 1$ vector of regression coefficients associated with the $j^{th}$ component, for $j = 1, \cdots, k-1.$

### *Model Selection: Bayesian Information Criterion (BIC)*

Bayesian Information Criterion (BIC) is one of the information criterion used for model selection. The mathematical formula is given below:

$$BIC = -2InL + dIn(n)$$

**Where** d is the number of parameters in the mixture model, and L is the maximized value of the likelihood function for the estimated model. Where n is the number of observations. Hence, the model with the lowest measures of BIC was considered as the best model to the data. This information criteria is used to determine the number of supports (Components) in the populations.R package version 3.6.1 is used to determine the number of components and to draw graphs while STATA version 15 is employed to run mixture of gamma regression.

### Result and Discussion

Table 1 shows the descriptive statistics of length of stay (LOS) and the predictors: Age, parity, number of visit, mother's weight, baby's weight, number of procedure and number of diagnosis. The minimum and maximum of parity are 0 and 10 respectively with mean of 2.26 numbers of children. The minimum and maximum of number of visit are 0 and 12 respectively with mean of 3.00. Similarly the minimum and maximum of mother's weight are 53 and 100 with mean of 57.478. The minimum and maximum of baby's weight are 2.0 and 5.1 with mean of 2.646.

**Table 1: Descriptive statistics of the variables**

| | Min | Max | Mean | Std. Dev. |
|---|---|---|---|---|
| LOS | 1 | 18 | 1.83 | 2.45 |
| Parity | 0 | 10 | 2.26 | 1.72 |
| Number of Visit | 0 | 12 | 3.00 | 3.08 |
| Mother's Weight | 53.0 | 100.0 | 57.49 | 11.31 |
| Baby's Weight | 2.0 | 5.1 | 2.64 | 0.54 |

In other to confirm the nature of MLOS, we plotted histograms (Figs. 1a and 2a), box plots (Figs. 1a and 2b), frequency curve (Figs. 1c and 2c) and lastly the normal Q-Q plots (Figs. 1d and 2d). All the charts and the curves are in support of Skewness of the dataset. Therefore, these results justify the use of gamma density as distributional properties of MLOS.

Table 2 shows the values of BIC for fitting gamma mixture model (FMM) with number of support(s) or components k =1, 2 or 3 on dataset for maternity length of stay for the two groups of women (i.e. those less than 25 years and 25 years and above). In age group less than 25 years, the BIC indictor supported the two-component Gamma mixture model. In other words, two-component Gamma Mixture Model is best fit the data with the lowest BIC values of 715.474. Similarly two – component gamma mixture is best fit with minimum value of BIC = 493.001, for women under age 25 years and above. This implies that we have two subpopulations in each group of women which correspond to short-stay and long-stay components respectively, which are the latent classes determined from the data. For women age less than 25 years, the proportion of patients (women) having short-stay is, $\pi_1$ = 0.79 (79%) with an average length of stay, $\mu_1$ = 1.34 days while the proportion of patients in longer stay , $\pi_2$ = 0.21 (21%) with an average length of stay, $\mu_2$ = 5.36 days. Table 3 is on women between age 25 years and above, shows that proportion of patients in short-stay component, $\pi_1$ = 0.80(80%) of the population with an average of $\mu_1$ = 1.53 days while proportion in the longer stay component, $\pi_2$ =0.20 (20%) of the population with an average length of stay, $\mu_2$ = 4.39 days. It is evident from these results that difference exists between the lengths of stay in the two components for the two groups of women.

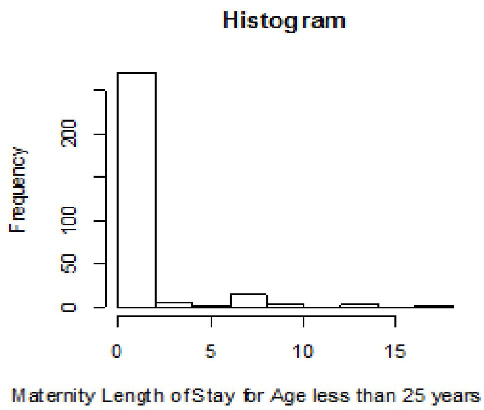


**Fig. 1a: Histogram for LOS**

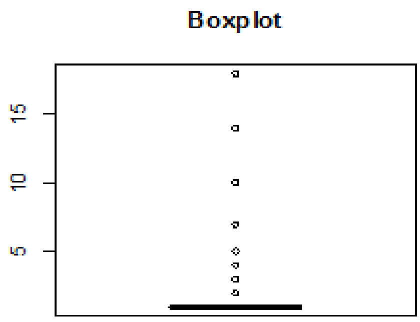


**Fig. 1b: Box Plot for LOS**

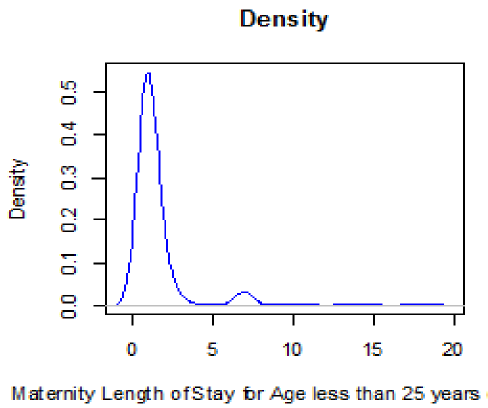


**Fig. 1c: Normal Curve Plot of LOS**

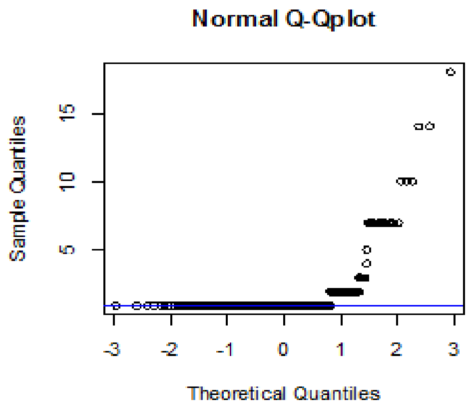


**Fig. 1d: Normal Q-Q Plotfor LOS**


**Fig. 2a: Histogram for LOS**

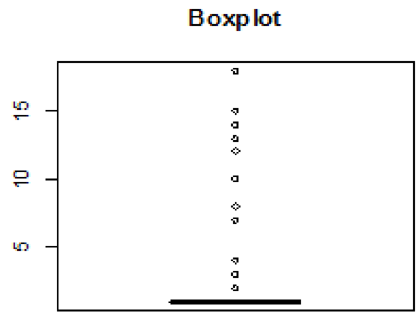


**Fig. 2b: Box Plot for LOS**

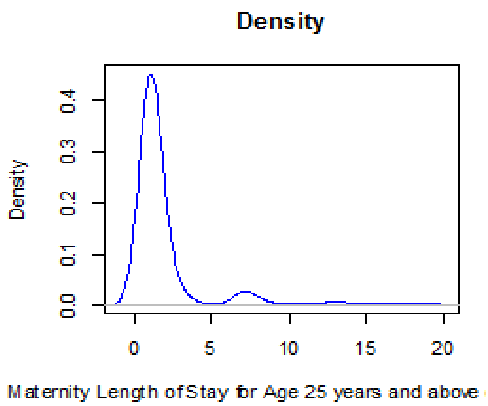


**Fig. 2c: Normal Curve Plot of LOS**

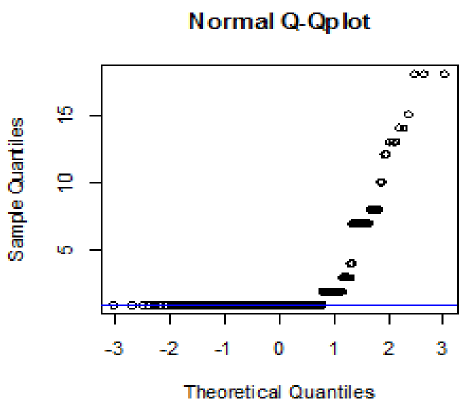


**Fig. 2d: Normal Q-Q Plotfor LOS**

**Table 2: Parameter estimate for the mixture of gamma regression for age less than 25 years**

| Number of Component | Parameter Estimate | BIC |
|---|---|---|
| 1 | $\pi_1 = 1.00$ $\alpha_1 = 1.53$<br>$\mu_1 = 1.93$ $\beta_1 = 0.79$ | 546.201 |
| 2 | $\pi_1 = 0.79$ $\pi_2 = 0.21$<br>$\alpha_1 = 4.39\times10^{13}$ $\alpha_2 = 1.88$<br>$\beta_1 = 4.39\times10^{13}$ $\beta_2 = 0.35$<br>$\mu_1 = 1.34$ $\mu_2 = 5.36$ | 493.001* |
| 3 | $\pi_1 = 0.78$ $\pi_2 = 0.19$ $\pi_3 = 0.03$<br>$\alpha_1 = 4.39\times10^{13}$ $\alpha_2 = 2.66$ $\alpha_3 = 30.00$<br>$\beta_1 = 4.39\times10^{13}$ $\beta_2 = 0.64$ $\beta_3 = 2.08$<br>$\mu_1 = 1.00$ $\mu_2 = 4.12$ $\mu_3 = 14.43$ | 502.001 |

*best fit

**Table 3: Parameter estimate for the mixture of gamma regression for 25 years and above**

| Number of Component | Parameter Estimate | BIC |
|---|---|---|
| 1 | $\pi_1 = 1.00$ $\alpha_1 = 1.97$<br>$\mu_1 = 1.68$ $\beta_1 = 1.17$ | 769.736 |
| 2 | $\pi_1 = 0.80$ $\pi_2 = 0.20$<br>$\alpha_1 = 4.39\times10^{13}$ $\alpha_2 = 2.12$<br>$\beta_1 = 4.39\times10^{13}$ $\beta_2 = 0.48$<br>$\mu_1 = 1.53$ $\mu_2 = 4.39$ | 715.474* |
| 3 | $\pi_1 = 0.79$ $\pi_2 = 0.19$ $\pi_3 = 0.01$<br>$\alpha_1 = 4.39\times10^{13}$ $\alpha_2 = 2.68$ $\alpha_3 = 40.00$<br>$\beta_1 = 4.39\times10^{13}$ $\beta_2 = 0.69$ $\beta_3 = 2.64$<br>$\mu_1 = 1.21$ $\mu_2 = 3.86$ $\mu_3 = 15.14$ | 752.469 |

*best fit

Tables 4 shows the parameter estimates of risk factors of MLOS and their corresponding P-values in brackets for the two - component Gamma Mixture Model (GMM). A cursory look at the table shows that some of the covariates included in the analysis have a statistically significant bearing on length of stay (LOS). For instance, in age less than 25 years, hospital type, location, educational qualification and mode of delivery in shorter stay component while hospital type, educational qualification, mode of delivery, mother's weight have significant effect on longer stay component. The results also indicated that those who attended public hospital in component stay- shorter have odd ratio of $2.3011$. Also, pregnant women who had first school leaving certificate, SSCE, NCE/ND, B.Sc/HND, others qualifications in component stay- shorter after delivery have odds ratios of $0.8516$, $0.8047$, $0.5623$, $0.7184$, $0.1596$ respectively. It is noted in the two groups of women that the mode of delivery through cesarean in both short stay component as well as long-stay component is significant. The patient who delivers through cesarean stays longer in the hospital with odd ratio 2.0657.

**Table 4: Two-component mixture of gamma parameter estimates in short-stay and long -stay components for the Age less than 25 years**

| | Parameters | Reference Category | Short – Stay Component *Estimate (PValue)* | Long – Stay Component *Estimate (PValue)* |
|---|---|---|---|---|
| | Constant | | 2.7919 (0.000) | 1.0986 (0.000) |
| **Hospital Type:** | Private | Public | 0.8334* (0.000) | 2.11e-06* (0.000) |
| **Location:** | Urban | Rural | -1.44e-07* (0.009) | -1.27e-07 (0.361) |
| **Occupation:** | Business | Housewife | 0.4987 (0.075) | -2.19e-07 (0.417) |
| | Civil Servant | | 0.0015 (0.993) | 3.39e-07 (0.194) |
| **Educational Qualification:** | Primary Certificate | No Education | -0.1608 (0.316) | -1.86e-08 (0.908) |
| | S.S.C.E | | -0.2173 (0.223) | 1.23e-07 (0.438) |
| | NCE/OND | | -0.5758* (0.010) | 1.72e-07 (0.472) |
| | BSC/HND | | -0.3307 (0.476) | 8.57e-07* (0.040) |
| | Others | | -1.8349 (0.996) | 1.06e-06 (0.125) |
| Parity | | | 0.0440 (0.546) | 6.74e-09 (0.932) |
| **Model of delivery:** | Caesarean delivery (CS) | Normal | 0.7218* (0.000) | 0.7255* (0.000) |
| No of Visit | | | 0.0071 (0.702) | 3.59e-08 (0.105) |
| Mother Weight | | | -0.0132 (0.129) | -1.39e-08* (0.046) |
| Baby Weight | | | -0.2388 (0.122) | -0.0036 (0.951) |
| No of Procedures | | | 0.0438 (0.385) | 7.71e-08 (0.205) |
| No. of Diagnosis | | | -0.0728 (0.169) | 0.08271 (0.095) |

** Significant at 5%*

**Table 5: Two-component mixture of gamma parameter estimates in short and long stay component for Age 25 years and above**

| | Parameters | Reference Category | Short – St ay Component *Estimate(PValue)* | Long – Stay Component *Estimate (PValue)* |
|---|---|---|---|---|
| | Constant | | 2.5188 (0.000) | 2.2387* (0.000) |
| **Hospital Type** | Private | Public | 0.4186 (0.058) | 0.1835* (0.006) |
| **Location:** | Urban | Rural | 0.1270 (0.310) | -0.5361* (0.018) |
| **Occupation** | Business | Housewife | 0.1251 (0.434) | 0.1397* (0.034) |
| | Civil Servant | | -0.0352 (0.750) | -0.0092 (0.882) |
| **Educational Qualification** | Primary Certificate | No Education | -0.0097 (0.951) | 0.0631 (0.357) |
| | S.S.C.E | | 0.0781 (0.571) | 0.0368 (0.542) |
| | NCE/OND | | 0.2984* (0.021) | 0.1481* (0.012) |
| | BSC/HND | | -0.0149 (0.932) | -0.0380 (0.657) |
| | Others | | -0.0433 (1.000) | 0.7968 (0.051) |
| Parity | | | -0.0603 (0.117) | -0.0079 (0.519) |
| **Model of delivery** | Caesarean delivery (CS) | Normal | 1.1632* (0.000) | 1.9777* (0.000) |
| No of Visit | | | 0.0107 (0.606) | 0.00003 (0.997) |
| Mother Weight | | | -0.0058 (0.197) | -0.0051* (0.008) |
| Baby Weight | | | -0.1203 (0.539) | -2.98e-06* (0.000) |
| No. of Procedures | | | 0.2115* (0.000) | 0.0817* (0.000) |
| No. of Diagnosis | | | -0.0184 (0.708) | -0.0196 (0.358) |

Table 5 shows the parameters' estimates and P-value of risk factors included in the two- component Gamma Mixture Model (GMM) for patients under the age 25 years and above. A critical look at the tables shows that some of the covariates included in the analysis are statistically significant for predicting length of stay (LOS).

There are 3 risk factors that are significantly affected the length of stay in short stay component. Namely: educational qualification, mode of delivery and number of procedures while 9 covariates have significant effect on long-stay component. They are hospital type, location, occupation, educational qualifications, and mode of delivery, mother's weight, baby's weight and number of procedures. For short-stay patient, the odd ratio of stay longer in private hospital is 1.5198 compared to public hospital which shows that patient in public hospital had shorter stay than patient from private hospital. In short-stay component, the civil servant women had an odd ratio of 0.9654 , shows a better chance of staying shorter after delivery than housewife and business women while in the long-stay component, business women had tendency of staying longer after delivery than housewife and civil servant. In the long-stay component, urban-based patients have shorter LOS compared to rural patients with odd ratio 0.5850. The result also shows that a patient who went through cesarean delivery has a higher probability of belonging to long-stay with odd ratio 7.2261. Clinical measures such as number of procedures have significant effect on the maternity length of stay. In particular, an increase in the number of procedures tends to increase the probability of belonging to the long-stay component.

**Conclusion**

The general observation is that the sets of significant factors affecting maternity LOS appear to be different between the short and long stay subgroups. Pregnant women from rural areas tend to stay longer in the hospital. There might be some possible reasons; the patients from distant areas may have their admission to hospital due to logistical problems such as difficulties in arranging appropriate modes of transport to remote settlements. Also, fewer clinical hospitals in rural areas could also contribute. These may lead to further complication and consequently late discharge. These findings are consistent with the literature (Lee & Codde, 2000). The study revealed that patient who attended private hospital tends to stay longer than public hospitals. This might be that public health institution are more equipped that private hospitals .The longer LOS observed in Caesarean patients relative high than those with normal delivery is probably due to the additional time required to recover sufficiently after the surgical intervention (Lee *et al.*, 2002). The common factors associated with maternity length of stay for both mother with age less than 25 years and age 25 years above are hospital type, educational qualification, mode of delivery and number of procedures, but the number of procedures had more significant effect on maternity length of stay than others. In particular, an increase in the number of procedures tends to increase the probability of belonging to the long-stay sub-population as well as prolonging the stay within that group. This finding is congruent with the literature (Ng *et al.*, 2003; Singh & Ladusingh, 2010). Finally, the mixture of two-component gamma mixture regression model fitted into data of maternity length of stay has indicated an existence of heterogeneous subpopulations in each the categorical groups (age group less 25 years and group age 25 years and above). Also, the number of risk factors associated with MLOS are more for patients in stay-longer component than those in short-stay component in age group 25 and above. This is an indication of more financial allocation and physical resources needed for age group 25 years and above.

**Conflict of Interest**

The authors declare that there is no conflict of interest related to this work.

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