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Bayesian variable selection in Tobit quantile regression

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Abstract : The paper explores the quantile regression model, a crucial tool in various scientific fields, focusing on characterizing conditional quantile forms in Tobit regression by estimating appropriate parameters from the lasso Bayesian theorem aspect. The study employs a novel Bayesian hierarchical priors model for the Gibbs sampler procedure, combines Rayleigh distribution with standard exponential, and investigates Bayesian quantile regression estimation for the Tobit model using MCMC and Gibbs sampler techniques. . The study employs a novel Bayesian hierarchical priors model for the Gibbs sampler procedure, combines Rayleigh distribution with standard exponential, and investigates Bayesian quantile regression estimation for the Tobit model using MCMC and Gibbs sampler techniques.The recommended technique outperforms other regression models in terms of variable selection prior due to its lower mean absolute error and mean square error.

Introduction: Statistics uses mathematics to evaluate data across various fields, with regression models being popular for elucidating relationships between variables, primarily utilizing covariate data for average value determination The median regression model is used for determining the median value of a response variable, and quantile regression has evolved into a sophisticated statistical analysis tool, challenging the mean and median regression models. Research on fading regression models has focused on deciding which predictor variables to include and exclude due to the abundance of factors, highlighting the need for efficient statistical methods. Red data, found in various scientific fields, often contains limited response variables. Tobit regression analyses focus on these, considering the reopener variable and limiting the observations.

This paper examines Bayesian Tobit quantile regression, a popular approach for analyzing response and predictor variables. It introduces the idea of using a new prior distribution to improve the Bayesian approach.

The limitations of response variable observation are present in a wide range of disciplines (economics, health, finance, etc.), and in the interim, the numerous predictor variables in the underlying phenomena, along with a breach of certain assumptions regarding the use of multiple line regression, We suggested using the Bayesian Tobit quantile regression model to address the aforementioned issue in light of all of these issues.

1. suggests utilizing the Bayesian approach and the scale-mixture of Rayleigh to express the relevant parameter in Tobit quantile regression.
2. To use lasso in Tobit quantile regression in conjunction with the Bayesian variable selection process
3. To use the MMAD criterion at various quantile levels to compare the suggested regression model that was created in objectives (1) and (2) with a few other regression models that are currently in use.

The novel Gibbs sampler approach for the Bayesian quantile regression was presented by Kozumi and Kobayashi (2011). They used a scale combination of a normal distribution mixed with an exponential distribution to describe the asymmetric Laplace distribution (ALD).

Taking into account the scale combination that Mallick and Yi (2014) provided, Alhusseini developed a novel Bayesian estimation and variable selection in Lasso quantile regression in 2017. A new, straightforward, and effective Gibbs Sampler algorithm is introduced. An investigation of real data and simulation demonstrates how well the suggested model performs.

Alhusseini (2018) suggested employing the scale mixture introduced by Mallick and Yi (2014) in the Tobit quantile regression from a Bayesian perspective. The variable selection problem was examined in this work utilizing both actual data analysis and simulation studies.

In 2020, Flaih et al. proposed a new Bayesian Lasso through developed of a new hierarchical model by using new scale mixture of the Laplace distribution, which is a mixture of normal mixing with Rayleigh distribution,
In order to ensure that the posterior distribution of the parameter estimate has just one mode, we combine the scaled Rayleigh distribution on the variances with a conventional exponential distribution in this thesis to provide a new Bayesian method to the TQR model. Our contribution is a paper that studies the Lasso Tobit quantile regression model.

2. Bayesian quantile regression

Koenker and Machado's (1999) concept of reducing the empirical check function equates to maximizing the probability function of an asymmetric Laplace distribution, a fundamental concept in Bayesian quantile regression by:
$f(\varepsilon\backslash\sigma,\vartheta)=\frac{\vartheta(1-\vartheta 0}{\sigma}\exp(-p\vartheta(\varepsilon))$ ……….1.1
Where $p_{\vartheta}(\varepsilon)=\varepsilon\big(\vartheta-1(\varepsilon<0)\big)\backslash\sigma.\tau$
The asymmetric Laplace distribution, with a sleekness parameter τ, is prone to mistakes with equal samples size (n), and is independent (i.i.d.) Benoit and Van den Poel (2012) used a method for determining quantile regression parameters for binary data, but Yu and Moyeed (2001) suggested a scaling parameter and Bayesian quantile regression in their work. Yu and Stander developed a Bayesian approach for Tobit quantile regression, which Geraci and Bottai recommend using alongside asymmetric Laplace likelihood for longitudinal data modeling.
$\varepsilon_i=\alpha u_i+\sqrt{\delta\sigma u_i z_i}$
Kozumi and Kobayashi (2011) introduced the Gibbs sampling approach for Bayesian quantile regression, utilizing an asymmetric Laplace distribution, which distributes mistakes exponentially with parameters, enhancing accuracy. The phrase $(\frac{\sigma}{\vartheta(1-\vartheta)}$ can be rewritten as where $z_i$is distributed with
$\alpha=1-2\vartheta$and$\delta=2.$ A new sampling method and flexible sampling from the posterior distribution are developed

3. Rayleigh-distributed

For random variables with nonnegative values, the Rayleigh distribution is a continuous probability distribution that is utilized in probability theory and statistics. It fits the two-degree-of-freedom chi distribution when scaling is used. In the distribution, Lord Rayleigh receives recognition. A Rayleigh distribution is commonly observed when the directional components and overall magnitude of a vector are related in the plane. For example, when wind speed is investigated in two dimensions, the Rayleigh distribution appears by default. The Rayleigh distribution will be used to depict the overall wind speed (vector magnitude). if every component has a zero mean, is normally distributed with equal variance, and is uncorrelated. When random complex numbers are used, the distribution takes on a second form. In this case, the real and imaginary components of the numbers have independent, identical Gaussian distributions with a zero mean and equal variance. The absolute value of the complex number is then Rayleigh-distributed. The random variable x is associated with a Rayleigh distribution with a shape parameter σ, represented by the notation x Rayleigh(σ). The following is the probability density $(x>0$):$\frac{x}{\sigma^2}e^{-x^2}/_{2\sigma^2}$

$$\mathrm{E}(x)=\int_0^{\infty}x\frac{x}{\sigma^2}\exp\left(\frac{x^2}{2\sigma^2}\right)dx$$

Solving the integral for you gives the Rayleigh expected value of

$$\sigma\sqrt{(\pi/2)}$$

The variance of a Rayleigh distribution is derived in a similar way, giving the variance formula of:
Var(x) = $\sigma^2((4-\pi)\backslash 2)$

4. the Bayesian Hierarchical model

Following is the hierarchy of how the different features were previously distributed:

$\boldsymbol{y_i=\acute{x}_\iota\beta+(1-2s)z_i+\sqrt{2\sigma^{-1}}z_i\varepsilon_i}$**………1.2**

$$\boldsymbol{y_i=max\{y^0,{y_i}^*\}\quad ,i=1,,,,,n}$$
$$\boldsymbol{y_i^*\backslash\beta,z_i,\sigma\sim N}$$
$$\boldsymbol{\acute{x}_\iota\beta+(1-2s)z_i\,,2\sigma^{-1}z_i}$$
$$\boldsymbol{z_i\backslash\sigma\quad\sim exp[s(1-s)\sigma]}$$
$$\boldsymbol{\beta_i\backslash s\sim N(0,\sigma^2A_\tau)}$$

$$A_\tau = diag(\tau_1, \tau_2, , , , , , \tau_p)$$
$$\tau \sim exp(\alpha)$$

$$\sigma^2 \sim (\sigma^2)^{a-1} exp(-b\sigma^2)$$
$$\alpha \sim \alpha^{c-1} exp(-d\alpha)$$

The MCMC algorithm steps are as follows:

1.updale y_i^*:using the following conditional distribution for general y_i^*as follows:

$$y_i^* \backslash y_i, \beta, \sigma \sim \begin{Bmatrix} g(y_i) \ \ if y_i > y_i^0 \\ N(\acute{x}_\iota\beta + (1-2s)z_i, 2\sigma^2 z_i) I(y_i^* < y_i^0 \\ 0 \qquad\qquad other e\ wise \end{Bmatrix} \quad ...1.3$$

2.updale β: the full conditional distribution for A truncated normal distribution with mean and variance is as follows

$$\widetilde{B} = \frac{\sum_{i=1}^{n} \sigma(x_i \acute{x}^i)}{2z_i} + B_0^{-1}$$
$$mean = \widetilde{\beta} = \widetilde{B}\left[\sum_{i=1}^{n} \sigma(x_i(y_i^* - (1-2s)z_i))\backslash 2z_i + B_0^{-1}\beta_0\right]$$
$\beta \sim Normal\,(\widetilde{\beta}, \widetilde{B})$**.....and** $\beta_0 = 0$

3.updale σ the full conditional distribution of σ is defined as Gamma distribution with shape parameter $a + \frac{3n}{2}$ and rate parameter

$$\sum_{i=1}^{n} [(y_i^* - \acute{x}_i\beta - (1-2s)z_i)^2 \backslash 2z_i + s(1-s)z_i] + p$$

4.the full condition of α is Gamma distribution

$$\pi(\alpha\backslash\beta) \propto \alpha^{2p}.\, exp\left[-\alpha \sum_{j=1}^{p} |\beta j|\right].\, \pi(\alpha)$$

$$\propto \alpha^{2p} exp\left[-\alpha \sum_{j=1}^{n} |\beta j|\right].\frac{\alpha^{c-1}}{\Gamma_c} b^c e^{-d\alpha}$$
$$\propto \alpha^{2p+c-1} exp\left[-\alpha \sum_{j=1}^{p} |\beta j| - d\alpha\right]$$
$$\propto \alpha^{2p+c-1} exp\left[-\alpha(d + \sum_{j=1}^{p} |\beta j|)\right]$$

$\alpha \sim Gamaa\ shape\ parameter(2p + c and\ rate\ \sum_{j=1}^{p} |\beta j| \ldots.$(amira sifr 2022)

5.updal z_i the full condition distribution of z_i is inverse gamma with mean $(y_i^* - x^t{}_i\beta)^{-1}$ and shape parameter $(\sigma\backslash 2)$

5. Simulation study

In this section of the study, we use simulated situations to assess how well our proposed strategy performs. We compared the Bayesian methods (T.Q. regression) with our suggested technique New BL Tobit Q Reg. Powell (1986) presents the T-Q regression, a non-Bayesian technique. By using the function (BAnet) of the quantreg package, which was introduced by Koenkers (2011), The new Bayesian lasso in T Q Regression was inspired by Alhusseini (2017) and referred to as the New B Tobit Q Reg. Two criteria have been used to rank the approaches that have been utilized: the mean absolute error referred (MMAD) and the standard deviation referred (S.D.). We take into consideration the following four quantile levels: ϑ = 0.30, ϑ = 0.60 $\boldsymbol{and}$ ϑ =0.90 for every situation in the simulation. Three distinct distributions were used to create the random error ($\varepsilon_i j$ = 1, 2, …, $\boldsymbol{n}$): the conventional normal distribution ($\boldsymbol{\varepsilon i} \sim \boldsymbol{N}$(2,3)), the Laplace distribution with mean(0) and variance (1) ($\boldsymbol{\varepsilon i} \sim \boldsymbol{N}$(0.1)), and the ($x^2$) distribution with five degrees of freedom. Our data simulation was created using the following model

$$y_i = \max(0, y^*)$$
$$yi^* = x_i^t \beta_\vartheta + \varepsilon_i$$

Where: After running our suggested method's algorithm for 11,000 iterations, the first 1000 were discarded burn in. To assess our suggested approach in comparison to alternative approaches in Two simulation scenarios in the same field have been employed. We will utilize four sample sizes in our study:(n =50, n =100, n =

150, and n = 200) The independent variables produced by using var-cov ($R_I G_J$)=$(0.5)^{I+J}$ and mean (2) in multivariate normal

6. Simulations Scenario

We demonstrate the efficacy of our suggested strategy with sparse cases in our first simulation. As a result, the correct model is given by

$$y_i = \max(0, y^*)$$

Where $y^* = x_{1i} + 2x_{4i} + 1x_{6i} + \varepsilon_i$

The actual values of the aforementioned model are as follows: $\boldsymbol{\beta}$ =$(1,0,0,2,0,1,0,0)^t$provides an overview of the standard deviation and mean absolute error for our suggested approach as well as the other two approaches for comparison. The mean absolute error (MMAD) obtained using our suggested technique was much less than the MAE obtained using the other two methods (BAnet, New B Tobit Q Reg), taking into account all error distributions, quantile levels, and sample sizes. Additionally, using all error distributions and quantile levels under consideration, the standard deviation (S.D.) obtained by our suggested technique was significantly less than the S.D. determined by the other two methods(BAnet, New B L Tobit Q Reg). Thus, when compared to the other two ways (BAnet , New B LTobit Q Reg), our suggested method performs more correctly

First simulation

Table.1. The MMADs and standard deviations for Simulation one.

	Methods	ϑ	$\varepsilon_i \sim N(2,3)$	$\varepsilon_i \sim laplace(0,1)$	$\varepsilon_i \sim \chi^2_{(5)}$
n=50	**BAnet**	0.30	0.842(0.478)	0.845(0.490)	0.942(0.623)
	BAnet	0.60	0.875(0.590)	0.742(0.363)	0.971(0.545)
	BAnet	0.90	1.258 (0.801)	0.964 (0.647)	0.891 (0.560)
	New BL Tobit Q Reg	0.30	0.712(0.467)	0.898(0.599)	0.832(0.610)
	New BL Tobit Q Reg	0.60	0.812 (0.599)	0.714(0.505)	0.924(0.601)
	New BL Tobit Q Reg	0.90	1.007 (0.750)	0.965 (0.500)	0.829 (0.567)
	BRL Tobit Q Reg	0.30	0.545(0.205)	0.641(0.211)	0.721(0.267)
	BRL Tobit Q Reg	0.60	0.624(0.105)	0.562(0.347)	0.641(0.242)
	BRL Tobit Q Reg	0.90	0.755 (0.064)	0.732 (0.067)	0.512 (0.594)
n=100	**BAnet**	0.30	0.768(0.422)	0.823(0.582)	0.791(0.492)
	BAnet	0.60	0.924(0.683)	0.681(0.482)	0.823(0.601)
	BAnet	0.90	0.964 (0.562)	0.811 (0.734)	0.732 (0.651)
	New BL Tobit Q Reg	0.30	0.712(0.467)	0.898(0.599)	0.832(0.610)
	New BL Tobit Q Reg	0.60	0.812 (0.599)	0.714(0.505)	0.924(0.601)
	New BL Tobit Q Reg	0.90	1.007 (0.750)	0.765 (0.500)	0.829 (0.567)
	BRL Tobit Q Reg	0.30	0.545(0.315)	0.856(0.451)	0.573(0.267)
	BRL Tobit Q Reg	0.60	0.624(0.175)	0.786(0.547)	0.563(0.383)
	BRL Tobit Q Reg	0.90	0.555 (0.163)	0.792 (0.404)	0.571 (0.345)

n=150	**BAnet**	0.30	0.953 (0.451)	0.845 (0.544)	1.023 (0.838)
	BAnet	0.60	0.856 (0.581)	0.791 (0.627)	0.910 (0.571)
	BAnet	0.90	0.892 (0.610)	0.832 (0.501)	0.985 (0.631)
	New BL Tobit Q Reg	0.30	0.781 (0.451)	0.761 (0.361)	0.862 (0.631)
	New BL Tobit Q Reg	0.60	0.921 (0.574)	0.723 (0.674)	0.636 (0.584)
	New BL Tobit Q Reg	0.90	0.623 (0.428)	0.763 (0.430)	0.581 (0.294)
	BRL Tobit Q Reg	0.30	0.562 (0.373)	0.528 (0.305)	0.473 (0.219)
	BRL Tobit Q Reg	0.60	0.720 (0.423)	0.624 (0.328)	0.629 (0.219)
	BRL Tobit Q Reg	0.90			
n=200	**BAnet**	0.30	0.845 (0.396)	0.79 6(0.395)	0.934(0.571)
	BAnet	0.60	0.734 (0.471)	0.684 (0.473)	0.891 (0.483)
	BAnet	0.90	0.834 (0.505)	0.681 (0.417)	0.862 (0.471)
	New BL Tobit Q Reg	0.30	0.793 (0.435)	0.694 (0.382)	0.608 (0.511)
	New BL Tobit Q Reg	0.60	0.629 (0.393)	0.539 (0.330)	0.725(0.497)
	New BL Tobit Q Reg	0.90	0.629 (0.393)	0.539 (0.330)	0.725(0.497)
	BRL Tobit Q Reg	0.30	0.583 (0.426)	0.482 (0.206)	0.527(0.289)
	BRL Tobit Q Reg	0.60	0.506 (0.326)	0.369 (0.118)	0.482(0.195)
	BRL Tobit Q Reg	0.90	0.468 (0.154)	0.292 (0.097)	0.352(0.087)

Note: In the parentheses are SDs (1)Table

Sample size(50)at quantile level ϑ=0.30

From the above Table ,we see the value of MMAD and standard deviation are generated by our proposed method (BR L Tobit Q Rey)is much smaller than MMAD and standard deviation are generated via other Two method (BAnet and new BL Tobit Regression),From this result we can conclude the performance of our proposed method is a good compared with other Two method through three different there error

Sample size(50)at quantile level ϑ=0.60

As we can see from the above Table, our proposed method (BR L Tobit Q Rey) generates MMAD and standard deviation values that are significantly smaller than those generated by the other two methods (BAnet and new BL Tobit Regression). Based on these results, we can conclude that our proposed method performs well when compared to the other two methods through three different there errors

Sample size(50)at quantile level ϑ=0.90

As the above Table shows, the MMAD and standard deviation values generated by our recommended approach (BR L Tobit Q Rey) are substantially lower than those generated by the other two methods (BAnet and new BL Tobit Regression). These findings allow us to draw the conclusion that, when compared to the other

two techniques, our recommended strategy performs well via three distinct there mistakes

Sample size(100)at quantile level ϑ=0.30

We can see from the above table that the MMAD and standard deviation generated by our proposed method (BR L Tobit Q Rey) are significantly smaller than the MMAD and standard deviation generated by the other two methods (BAnet and the new BL Tobit Regression). Based on these results, we can conclude that our proposed method performs well when compared to the other two methods through three different errors.

Sample size(100)at quantile level ϑ=0.60

The MMAD and standard deviation values produced by our suggested method (BR L Tobit Q Rey) are significantly smaller than those produced by the other two methods (BAnet and new BL Tobit Regression), as can be seen in the above Table. Based on these results, we can conclude that our suggested method performs well when compared to the other two methods through three different there errors.

Sample size(100)at quantile level ϑ=0.90

The following table shows that, in comparison to the other two approaches (BAnet and the new BL Tobit Regression), our suggested method (BR L Tobit Q Rey) produces MMAD and standard deviation values that are noticeably reduced. We may

infer from these findings that, when compared to the other two ways, our suggested strategy performs well through three distinct mistakes

Sample size(150)at quantile level ϑ=0.30

As the table below demonstrates, our recommended method (BR L Tobit Q Rey) yields significantly lower MMAD and standard deviation than the other two approaches (BAnet and the new BL Tobit Regression). We may conclude from these facts that our proposed technique performs better than the other two methods because of three different defects.

Sample size(150)at quantile level ϑ=0.60

Our suggested approach, BR L Tobit Q Rey, produces MMAD and standard deviation values that are noticeably less than those produced by the other two methods, BAnet and new BL Tobit Regression, as we can see from the above Table. These findings allow us to draw the conclusion that, when measured against the other two approaches using three different threshold errors, our suggested strategy works well.

Sample size(150)at quantile level ϑ=0.90

The aforementioned table shows that, in comparison to the two other approaches, BAnet and the new BL Tobit Regression, our recommended strategy, BR L Tobit Q Rey, yields MMAD and standard deviation values that are significantly lower. Our conclusion can be drawn based on these results: our proposed

technique performs well when compared to the other two ways of employing three distinct threshold mistakes.

Sample size(200)at quantile level ϑ=0.30

Our recommended method, BR L Tobit Q Rey, yields significantly lower MMAD and standard deviation values than the two other ways, BAnet and the new BL Tobit Regression, as the above table illustrates. These results confirm our hypothesis that our proposed technique works well in comparison to the other two methods, which use three distinct threshold errors.

Sample size(200)at quantile level ϑ=0.60

As the above table shows, our suggested approach, BR L Tobit Q Rey, produces noticeably lower MMAD and standard deviation values than the two alternative approaches, BAnet and the new BL Tobit Regression. These findings support our premise that, when compared to the other two approaches that employ three different threshold errors, our suggested strategy performs well.

Sample size(200)at quantile level ϑ=0.90

As seen by the above Table, our suggested technique (BR L Tobit Q Rey) produces MMAD and standard deviation values that are significantly lower than those produced by the other two approaches (BAnet and new BL Tobit Regression). Our proposed

procedure outperforms the other two techniques by three separate there errors, as these data allow us to conclude

7. Real data

We use the Tobit quantile regression model in this phase of the study to examine the medical phenomenon. We collected 142 observations, one dependent variable, and eighteen independent variables from the balsam laboratory in the city of Al-Najf. The erythrocyte sedimentation rate, or ESR, is the dependent variable, while the following are the 18 independent factors:

$x1$: S.cholesterol Size. cholesterol referred
$x2$:, R.B.sugar
$x3$:, B.Urea
$x4$: S.Creatinine
x5:LDL Low-density lipoprotein referred
x6:HDL High-density lipoprotein referred
$x7$:Ca++ calcium referred x8:HC Hematocrit test referred
x9: Hb Hemoglobin blood referred
x10:PCVPacked cell volume referred
$x11$:WBC White Blood Cell referred
$x12$: E.S.R: Erythrocyte Sedimentation Rate
$x1$3:, Blood Group ,
x14:PLT Platelets count
$x15$:, PCT Platelet Count Test referred
$x1$6: MPV Mean Platelet Volume referred
$x1$7: Weight
$x1$8: Age.

We compare our suggested technique with two alternative ways (BAnet, New B Tobit Q Reg, and BR L Tobit Q Reg), much like our simulated scenario. Our suggested approach, along with the other two, is assessed using mean square error (MSE) and mean absolute error(MMAD). Table 3 includes the MSE and MMAD results. Table 3's results show that, for all quantile levels that were taken into consideration, the MMAD and MSE of our proposed technique were much lower than those generated by the other two approaches (BAnet New B Tobit Q Reg). Therefore, it is believed that our recommended strategy is better than other ways in the same field

	ϑ	**BAnet**	**New BL Tobit Q Reg**	**BRL Tobit Q Reg**
MSE (SD)	**0.30**	**17.651 (2.321)**	**14.431 (1.974)**	**8.562 (1.412)**
	0.60	**29.047 (4.934)**	**28.436 (3.241)**	**23.451 (2.341)**
	0.90	**31.721 (5.312)**	**30.193 (3.823)**	**17.932 (2.034)**

(2)

Based on real datasets and simulated techniques, we find that our methodology is the most effective for choosing variables and estimating coefficients in Tobit quantile regression. The tables below provide the parameter estimates of TQR for each of the quantile levels (ϑ=0.30, ϑ=0.60 andϑ=0.90)

Coefficients estimation of three methods via three quantile levels

Variables name	**Symbol variables**	**BAnet**			**New BL Tobit Q Reg**			**BRL Tobit Q Reg**		
	--------------	$\vartheta_1 = 0.30$	$\vartheta_2 = 0.60$	$\vartheta_3 = 0.90$	$\vartheta_1 = 0.30$	$\vartheta 2 = 0.60$	$\vartheta_3 = 0.90$	$\vartheta_1 = 0.30$	$\vartheta 2 0.60$	$\vartheta_3 = 0.90$
S.cholesterol	x_1	1.642	2.564	0.641	1.005	1.548	1.741	1.741	1.021	0.654
R.B.sugar	x_2	1.745	2.654	0.641	1.112	1.002	1.524	1.642	1.242	0.531
B.Urea	x_3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S.Creatinine	x_4	0.421	2.821	0.514	0.901	1.007	1.975	1.698	1.825	0.451
LDL	x_5	0.512	0.564	0.421	0.364	0.451	0.834	0.000	0.000	0.000
HDL	x_6	0.546	0.425	0.299	0.405	-0.764	0.874	0.641	0.654	0.842
CA++	x_7	-0.745	0.489	0.245	0.654	0.374	0.624	-0.745	0.523	0.851
HCT	x_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hb	x_9	0.812	0.845	0.451	0.414	0.452	0.628	0.901	0.524	0.421

		4								
PCV	$\mathbf{x_{10}}$	0.624	0.546	0.546	0.205	0.772	0. 745	0.824	0.845	0.299
WBC	$\mathbf{x_{11}}$	- 0.712	- 0.842	0.615	0.002	0.011	0.009	0.000	0.000	0.000
E.S.R	$\mathbf{x_{12}}$	0.845	0.674	- 0.645	0.297	0.862	0.462	0.624	0.906	0.204
Blood group	$\mathbf{x_{13}}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PLT	$\mathbf{x_{14}}$	- 0.842	0.682	0.468	1.421	0.754	0.426	0.645	0.423	0.514
PCT	$\mathbf{x_{15}}$	0.682	0.761	0.356	1.001	0.352	0.234	0.754	0.416	0.462
MPV	$\mathbf{x_{16}}$	0.761	0.901	0.332	0.006	0.028	0.023	0.000	0.000	0.000
Weight	$\mathbf{x_{17}}$	0.901	0.835	0.201	0.825	0.624	0.862	0.812	0.304	0.624
Age	$\mathbf{x_{18}}$	0.835	0.422	- 0.362	0.876	0.981	0.868	0.451	0.312	0.731

(3)

From table up we write down the following discussion

1. For .S.cholesterol (x_1)variable ,it is clew that the variable has positive effects on the response variable (y, erythrocyte sedimentation rate)are all quantile level and ender the estimation methods
2. For R.B sugar(x_2) variable ,also this variable (y)over all quantile levels
3. For variable (B.Urea,x_3);the results shat this variable has excluded from estimated model over all quantile levels ,we can see all the estimator method provide zero shamble to parameter of this variable which has no impact on x_3

4.For variable(x_4=S.Creatinine)under all quantile levels in all estimation method ,we can see the positives influence of this variable on y.

5.For variable (x_5=LDL),clearly the estimation method (BRL Tobit Q Reg)plays as variable selection method and excluded(removed)this variable frown the estimated model ,that is means ,the LDL variable has no impacts on y.

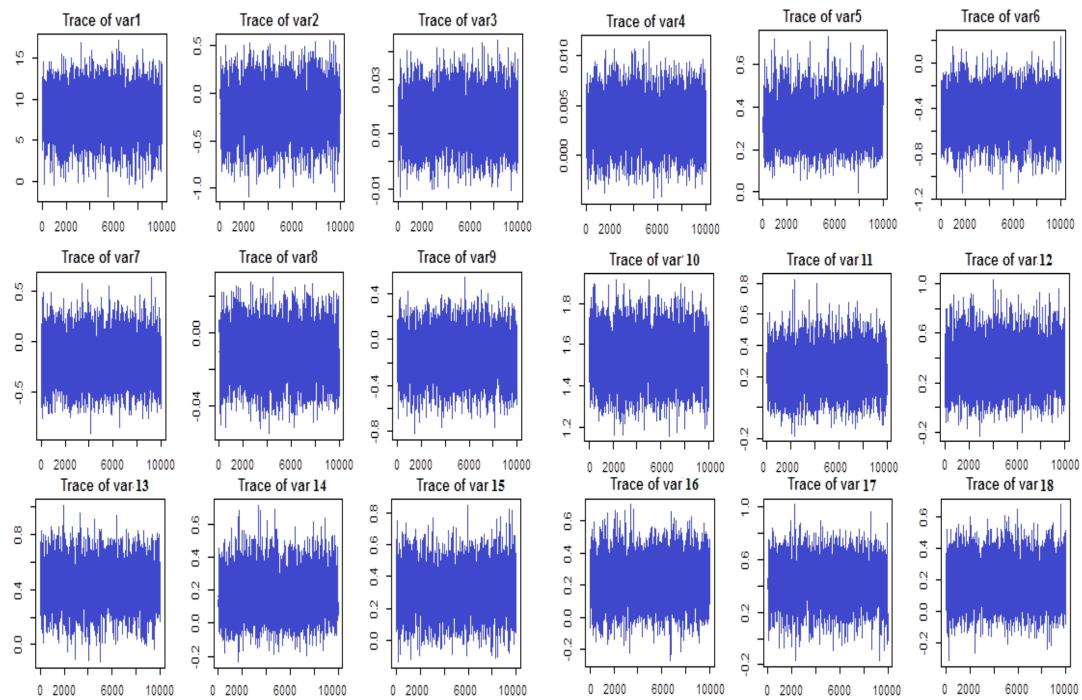
6.For variable (x_6=HDL),we can see this variable has in flounce on the response variable (y)over all the quantile method

7.For Variables

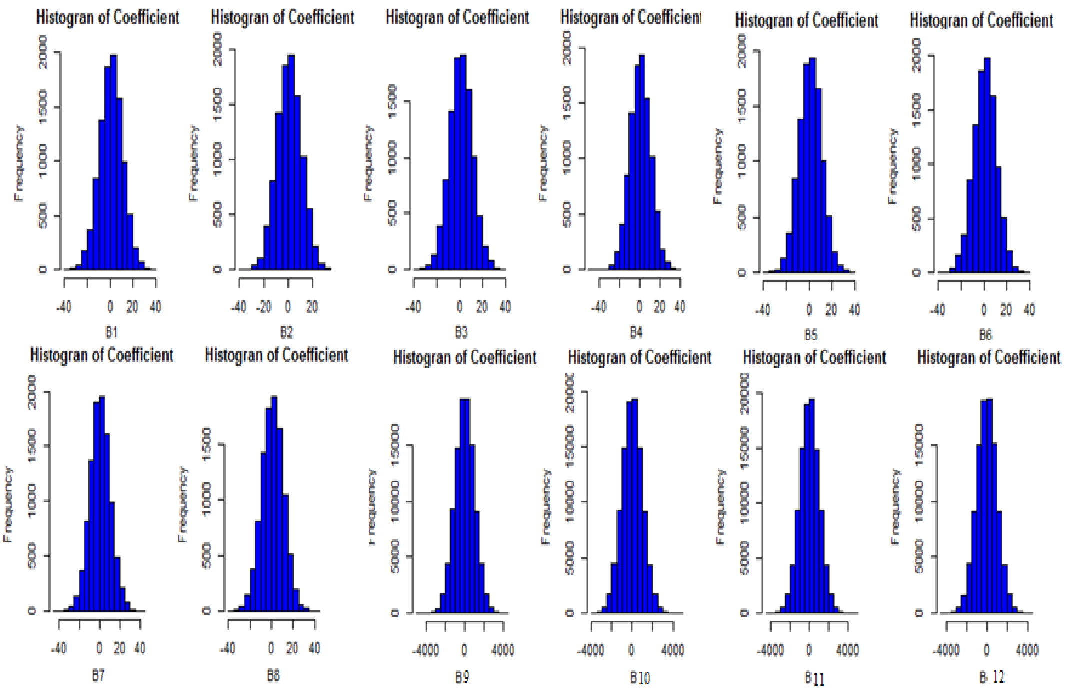
$$(x_7 = CA++, X_9 = Hb, x_{10} = PCV, X_{11} = WBC\ , X_{12} = ESR\ \ , X_{14} = PLT\ \ , X_{15} = PCT, X_{16} = MPV, X_{17} = weight, x_{18} = age),$$

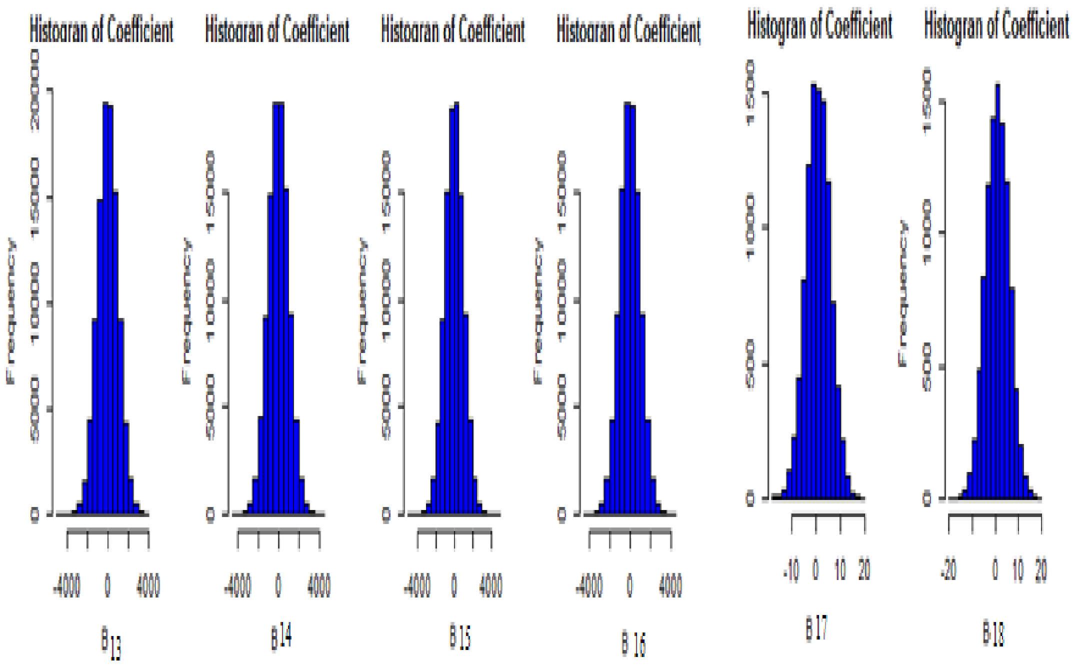
And under all the estimation methods in different quantile level ,the perform mince equally are likely and all these variable have influenced on the response variable (y).

For variable ($x_8 = HCT, x_{13} = Bloed\ group$) ,we can see that all the estimation method sets the impacts of these variable to zero in other words ,the variable ($x_8, and\ x_{13}$)have no influenced on the response variable (y), and then we removed these variable from the estimated model.



The predicted BR L Tobit Q Rey coefficients' trace plot should be displayed. Our technique is very convergent throughout each iteration, as the accompanying chart makes clear.





For the estimate of independent variables with eighteen parameters, a trace plot is displayed. show the estimated histogram for the BR L Tobit Q Rey coefficients. The following figure makes it clear that the coefficient estimation closely resembles the normal distribution. But the graph below

5. Conclusions

In conclusion, a new hierarchical approach to Bayesian tobit quantile regression was presented in this study. In comparison to previous algorithms, our Gibbs sampler algorithm was easy to use and efficient.

The simulation methodology and real dataset clearly show that our method(BRL Tobit Q Reg) lasso, performs well when compared to other approaches in the same field.

5.2 Suggestion

The researchers will be encouraged to develop other Bayesian tobit quantile regression models by using our method, with a new hierarchical(BRL Tobit Q Reg) which presents a new formula as an effective algorithm.

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