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COMPARISON BETWEEN BAYESIAN QUANTILE REGRESSION AND BAYESIAN LASSO QUANTILE REGRESSION FOR MODELING POVERTY LINE WITH PRESENCE OF HETEROSCEDASTICITY IN WEST SUMATRA

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ABSTRACT

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The poverty line is the threshold income level below which a person or household is considered to be living in poverty. The poverty line is a representation of the minimum rupiah amount needed to meet the minimum basic food needs equivalent to 2100 kilocalories per capita per day and basic non-food needs. According to data from the Central Bureau of Statistics (BPS), although the poverty rate in West Sumatra has decreased in recent years, the issue of poverty is still very relevant to be discussed and addressed. The issue of the poverty line is important to discuss because it is directly related to the welfare of people and the development of a country. For modeling the poverty line and its influencing factors, appropriate statistical methods are needed. This research is about the comparison of two methods, namely the Bayesian quantile regression method and Bayesian LASSO quantile regression. The two methods are compared with the aim of seeing which method produces the smallest error. Bayesian quantile regression is one method that can model data assuming heteroscedasticity violations. This study compares the ordinary Bayesian quantile regression method with penalized LASSO. These two methods are applied in modeling the poverty line in West Sumatra. The purpose of this study is to see the best method for modeling data. The data used amounted to 133 data points from BPS in the years 2017 and 2023. Model parameters were estimated using MCMC with a Gibbs sampling approach. The results show that the Bayesian LASSO method is superior to the method without LASSO. This is evidenced that the superior method produces the smallest MSE value, 0.208, at quantile 0.5. Model poverty line in West Sumatra is significantly influenced by per capita spending (X_1), Gross Regional Domestic Product (X_2), Human Development Index (X_3), Open Unemployment Rate (X_4), and minimum wages (X_5).

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1. INTRODUCTION

The poverty line is the threshold income level below which a person or household is considered to be living in poverty [1]. This poverty line is calculated based on per capita (per person) expenditure in a family, and is used to determine whether a person or family is considered to be living in poverty. Poverty is one of the main problems faced by many provinces in Indonesia, including West Sumatra. According to data from the Central Bureau of Statistics (BPS), although the poverty rate in West Sumatra has decreased in recent years, the issue of poverty is still very relevant to be discussed and addressed. The poverty line remains a major concern despite the decline in the poverty rate for several important reasons: persistent inequality, differential quality of life, uneven economic growth, insecure poverty reduction, and social policy targets. Poverty is not only limited to a lack of income but also includes limited access to basic services such as education, health, and infrastructure. Therefore, it is important to understand the factors that influence poverty so that policies can be better targeted.

One way to analyze and measure poverty is by using a poverty line. This poverty line is usually determined based on the income or consumption needed by an individual or family to fulfill basic needs. However, in a regional context, poverty measurement is not always uniform, and the uncertainty in the data and the variability between individuals or regions require a method that can capture this uncertainty more effectively. Regression is a statistical analysis technique used to measure the relationship between one or more independent (or predictor) variables and a dependent (or response) variable [2],[3],[4],[5],[6],[7],[8]. However, it is often found that our research data, which may be obtained from the field, does not meet the classical assumptions, namely the assumptions of normality, homoscedasticity, and the absence of multicollinearity and autocorrelation. One statistical method that can handle cases of violated assumptions is quantile regression [9].

Quantile regression is a very useful approach in this regard. Unlike the usual linear regression that only focuses on the mean of the data, quantile regression can estimate the relationship between the independent and dependent variables at different quantiles (for example, the 25th, 50th, and 75th quantiles)[10]. Quantile Regression (QR) is a statistical analysis method that was first introduced by Koenker [11]. Regression is used to quantify the relationship between the response variable and the covariates [12]. A quantile is a point in a dataset that divides the data into intervals with a certain proportion of the data falling below and above that point [9]. According to [3], quantile regression is a more comprehensive and flexible approach compared to ordinary linear regression as it focuses not only on the mean but also on the distribution of data across different quantiles (percentiles), providing deeper insights into the relationship between variables under different conditions. This technique is more robust to outliers and can reveal patterns that are not visible with traditional regression. The discussion related to this method has been studied by many researchers, including [13],[14].

QR is also discussed in [15], introducing a new distribution (0,1) and transforming positive random variables according to the Chen distribution with parameters estimated by quantile regression. The research conducted by [16] and [9] said that violations of the assumption of normality can be overcome with quantile regression. QR has the limitation that it requires a large sample, so it needs a Bayesian approach that can model small amounts of data and known as BQR [17],[18]. The Bayesian concept refers to an approach in statistics that uses Bayes' Theorem to update the probability of an event based on new evidence or information. The main components of the Bayesian concept are prior (Initial Probability), before obtaining new evidence, we have an initial belief or assumption about a hypothesis or parameter. This is called the prior probability, the second is the likelihood, likelihood measures how likely it is that we will get the evidence at hand if a particular hypothesis or parameter is true. The third is the posterior (conditional probability of the parameter), after combining the prior with the likelihood, we obtain the posterior probability, which is an updated estimate of the hypothesis after seeing the evidence. It turns out that research is growing, so the Bayesian method is not precise enough to obtain parameters either. So variable selection using LASSO was found.

One other method in the parameter estimation process is to use the LASSO (Least Absolute Shrinkage and Selection Operator) method is a technique in regression used to select important variables (feature selection) and simultaneously reduce model complexity by regularizing. The combination of BQR and LASSO is often referred to as (BLQR). LASSO is a type of linear regression that penalizes the size of regression coefficients to avoid overfitting and improve model generalization. Applications of quantile regression with Bayesian and LASSO are also presented [5]. Some studies using BLQR method include modeling the length of stay of covid 19 patients [19]. The same method is also used in modeling low birth weight [20]. Meanwhile, according to the Central Bureau of Statistics (BPS) of West Sumatra and literature review, the factors that influence the poverty line are percapita spending [21], gross regional domestic product [22], human development index [23], open unemployment rate [24], and minimum wages [25]. These factors will be used by researchers to model the poverty line. The modeling uses Bayesian quantile regression analysis without penalized LASSO and using LASSO. Based on previous literature studies and the advantages of the proposed method, researchers are interested in modeling the poverty line in West Sumatra using this method. Poverty lines in West Sumatra require special attention in the field of statistical modelling for several important reasons: economic inequality, social and economic change, diverse data, future poverty projections, and policy evaluation. Overall, statistical modeling provides a strong analytical framework for understanding poverty issues in West Sumatra and helps in designing more effective and evidence-based interventions.

2. RESEARCH METHODS

2.1 Quantile Regression

If a vector $y_i = (y_1, y_2, \dots, y_n)'$ is dependent variable and $x_i = (x_1, x_2, \dots, x_k)'$ is independent variable for $i = 1,2,\dots,n$ we can define the sample mean μ as solution, having succeeded in defining the unconditional quantiles as an optimization problem, it is easy to define conditional quantiles in an analogous fashion. Least squares regression offers a model for how we proceed to solve:

$$min_{\mu \epsilon \mathbb{R}} \sum_{i=1}^{n} (y_i - \mu)^2 \tag{1}$$

We obtain the sample mean, an estimate of the unconditional population mean $E[Y]$. If we now replace the scalar μ by $\boldsymbol{x_i'\beta}$ and solve:

$$min_{\beta\, \epsilon \mathbb{R}} \sum_{i=1}^{n} (y_i - x_i'\beta)^2 \tag{2}$$

$$min_{\beta \epsilon \mathbb{R}} \sum_{i=1}^{n} |y_i - x_i'\beta| \tag{3}$$

we obtain an estimate of the conditional expectation function $E(Y|x)$. So, the quantile regression equation model for quantile $0 < \tau < 1$ with n samples and k predictors for $i = 1,2,\dots,n$ is written in the form:

$$y_i = \beta_{0\tau} + \beta_{1\tau}x_{i1} + \beta_{2\tau}x_{i2} + \dots + \beta_{k\tau}x_{ik} + e_i. \tag{4}$$

With β_τ as parameter and e_i as residual. To find the parameter value $\widehat{\beta_\tau}$ is done by minimizing the equation [26]:

$$min_{\beta \epsilon \mathbb{R}} \sum_{i \epsilon i | y_i \geq x_i'\beta} \rho_\tau(y_i - x_i'\beta). \tag{5}$$

Where $\rho_\tau(u) = u(\tau - I(u < 0))$ is the *loss function*. In quantile regression, the loss function is specifically designed to estimate the conditional quantiles of the response variable. The goal of quantile regression is to minimize the sum of these asymmetric losses for all data points, thus finding predicted values corresponding to the desired quantiles with the equation:

$$\rho_\tau(\epsilon) = \varepsilon\big(\tau I(\varepsilon \geq 0) - (1 - \tau) I(\varepsilon < 0)\big) \tag{6}$$

$I\ (.)$ is an indicator function, which has a value of 1 when $I\ (.)$ is true and 0 if otherwise. Indicator function in quantile regression helps define the conditions under which different parts of the quantile loss function should be applied, thus enabling quantile regression to estimate specific quantiles of the conditional distribution.

2.2 Bayesian Quantile Regression

Bayesian quantile regression extends this framework by incorporating a probabilistic approach, using Bayesian inference to estimate the model parameters. Instead of point estimates for the quantile regression coefficients, Bayesian methods provide a distribution for the coefficients, reflecting uncertainty in the estimates. This is done by placing prior distributions on the regression coefficients and then updating these priors based on the data using Bayes' theorem. The combination [27] suggested that the process of minimizing the loss function of quantile regression. So, it corresponds to maximizing the likelihood function of the asymmetric Laplace distribution (ALD). The ALD distribution random variable uses a probability density function error for the quantile $f_\tau(\epsilon)$ [17]:

$$f_\tau(\epsilon) = \tau(1-\tau)exp\left(-\rho_\tau(\epsilon)\right) \tag{7}$$

With $0 < \tau < 1$ and ρ_τ is a loss function with as the error of the estimation, and is an indicator function. The ALD distribution is one of the continuous probability distributions. Suppose Z is a random variable with an exponential distribution ($Z \sim exp\ (1)$) and U is a random variable with a standard normal distribution $U \sim N\ (0,1)$. If ε is an ALD distributed random variable, then ε can be expressed in the following equation [28]:

$$\varepsilon = \theta z + pu\sqrt{z}. \tag{8}$$

Where $\theta = \frac{1-2\tau}{(1-\tau)\tau}$ and $p^2 = \frac{2}{(1-\tau)\tau}$. Likelihood function used in parameter $\boldsymbol{\beta}$ estimation for the τ^{th}quantile in the Bayesian quantile regression analysis is written [19]:

$$L(\boldsymbol{y}_i^*|\boldsymbol{\beta},\boldsymbol{\sigma},\boldsymbol{v}) = \left(\prod\nolimits_{i=1}^{n}(\sigma v_i)^{-\frac{1}{2}}\right)\left(\exp\left(-\frac{(y_i^* - (\boldsymbol{x}_i'\boldsymbol{\beta}_{\boldsymbol{\tau}} + \theta v_i))^2}{2p^2\sigma v_i}\right)\right). \tag{9}$$

With $\sigma > 0$ as the scale parameter and dan $v_i = \sigma z_i$ spreading exp *(σ)* distribution. The prior distributions used in this study are $\boldsymbol{\beta}_\tau \sim N(b_0, B_0)$, $v_i \sim \exp\ (\sigma)$ and $\sigma \sim IG(a,b)$. While posterior distributions for each prior are as follows:

$$(\boldsymbol{\beta}|,\sigma,v,\boldsymbol{y}\,) \sim N[(\boldsymbol{B}_{\boldsymbol{0}}^{-\boldsymbol{1}} + \boldsymbol{x}_{\boldsymbol{i}}(p^2\sigma v)^{-1}\boldsymbol{x}_{\boldsymbol{i}}')^{-1}\left(\boldsymbol{B}_{\boldsymbol{0}}^{-\boldsymbol{1}}\boldsymbol{b}_{\boldsymbol{0}} + \boldsymbol{x}_{\boldsymbol{i}}(p^2\sigma v)^{-1}x_i')^{-1}y - x_i(p^2\sigma v)^{-1}\theta v_i\right), \left(\boldsymbol{B}_{\boldsymbol{0}}^{-\boldsymbol{1}} + \boldsymbol{x}_{\boldsymbol{i}}(p^2\sigma v)^{-1}\boldsymbol{x}_{\boldsymbol{i}}')^{-1}\right]$$

$$(v_i|\boldsymbol{\beta},\sigma,\boldsymbol{y}) \sim GIG\left(\frac{1}{2},\left(\frac{y-x_i'\beta_\tau)^2}{p^2\sigma}\right),\left(\frac{2}{\sigma}+\frac{\theta^2}{p^2\sigma}\right)\right) \tag{10}$$

$$(\sigma|\boldsymbol{\beta},\boldsymbol{v},\boldsymbol{y}\,) \sim IG\left(a+\frac{3n}{2}, b + \sum_{i=1}^{n} v_i + \sum_{i=1}^{n} + \left(\frac{\left(y-(x_i'\beta_\tau+\theta v_i)\right)^2}{2p^2\sigma}\right)\right).$$

In determining the posterior distribution for the estimated parameters on the use of ALD as a *likelihood* function for the data, it is difficult to solve analytically [29]. To overcome this difficulty, a numerical approach is used with the help of the MCMC (Markov Chain Monte Carlo) algorithm, which is not only effectively used but also able to overcome complex analytical integration [27][30].

2.3 Bayesian LASSO Quantile Regression

Mathematically, estimates of Bayesian LASSO quantile regression parameters can be calculated by:

$$\boldsymbol{\beta}_{\boldsymbol{LASSO}} = \min_{\boldsymbol{\beta}\in\mathbb{R}} \sum_{\boldsymbol{i}=\boldsymbol{1}}^{\boldsymbol{n}} \boldsymbol{\rho}_{\boldsymbol{\tau}}(\boldsymbol{y}_{\boldsymbol{i}} - \boldsymbol{x}_{\boldsymbol{i}}'\boldsymbol{\beta}) + \boldsymbol{\lambda}\sum_{\boldsymbol{j}=\boldsymbol{1}}^{\boldsymbol{k}} |\boldsymbol{\beta}_{\boldsymbol{j}}|. \tag{11}$$

Where $\boldsymbol{\lambda}$ is a non-negative variable penalty coefficient. Prior distribution $\boldsymbol{\beta}_{\boldsymbol{\tau}}, \boldsymbol{\eta}^{\boldsymbol{2}}, \boldsymbol{\zeta}, \boldsymbol{\sigma}, \boldsymbol{s}, \boldsymbol{v}, \boldsymbol{\delta}$ used for n-th sample with k predictors according to for use in Bayesian LASSO quantile regression (BLQR) are:

$$\boldsymbol{f}(\boldsymbol{\beta}|\boldsymbol{\eta}^{\boldsymbol{2}}, \boldsymbol{s}_{\boldsymbol{j}}) = \prod_{\boldsymbol{j}=\boldsymbol{1}}^{\boldsymbol{k}} \int_{\boldsymbol{0}}^{\infty} \frac{\boldsymbol{1}}{\sqrt{\boldsymbol{2\pi s}_{\boldsymbol{j}}}} \,\mathbf{exp}\left(-\frac{\boldsymbol{\beta}_{\boldsymbol{j}}{}^{\boldsymbol{2}}}{\boldsymbol{2s}_{\boldsymbol{j}}}\right) \tag{12}$$

$$f(\eta^2|\delta,\zeta)=\frac{\zeta^\delta}{\Gamma(\delta)}\eta^{2(\delta-1)}\exp(-\zeta\eta^2),$$

$$f(\zeta|\delta)=1,$$

$$f(\sigma)=\sigma^{a_1^{-1}}\exp(-a_2\sigma),$$

$$f(s_j|\eta^2)=\frac{\eta^2}{2}\exp\left(-\frac{\eta^2}{2}s_j\right),$$

$$f(v_i|\sigma)=\sigma\exp(-v_i\sigma),$$

$$f(\delta|\zeta,\eta^2)=\frac{(\zeta\eta^2)^\delta}{\Gamma(\delta)}.$$

with $\eta=\sigma\lambda$, $\eta^2\sim Gamma(\eta^2,\zeta^{-1})$, $s=(s_1,\dots,s_k), i=1,2\dots k$, $v=(v_1,\dots,v_n)$, $\sigma>0$, $a_1>0$, $a_2>0$, $\eta^2>0$, $\zeta>0$, $\delta>0$. Based on Equation (12), the joint posterior distribution Bayesian LASSO quantile regression is obtained as follows:

$$f(\beta_\tau|\eta^2,\zeta,\sigma,s,v,\delta)\sim N\left(\frac{\frac{\sigma\sum_{i=1}^n\hat{y}_{ij}x_{ij}}{2v_i}}{\frac{1}{s_j}+\sigma\sum_{i=1}^n\frac{x_{ij}{}^2}{2v_i}},\frac{1}{\frac{1}{s_j}+\sigma\sum_{i=1}^n\frac{x_{ij}{}^2}{2v_i}}\right)$$

$$f(\eta^2|\beta_\tau,\zeta,\sigma,s,v,\delta)\sim Gamma\left(\zeta+k,v+\sum_{j=0}^k\frac{s_j}{2}\right), \tag{13}$$

$$f(v|\beta_\tau,\eta^2,\zeta,\sigma,s,v,\delta)\sim Gamma(\zeta,\eta^2),$$

$$f(\zeta|\beta_\tau,\eta^2,\sigma,s,v,\delta)\sim Gamma(\zeta,\eta^2),$$

$$f(v_i|\beta_\tau,\eta^2,v,\zeta,\sigma,s,v,\delta)\sim GIG\left(\frac{1}{2},\left(\frac{y_i-x_i'\beta_\tau)^2}{p^2\sigma}\right),\left(\frac{2}{\sigma}+\frac{\theta^2}{p^2\sigma}\right)\right),$$

$$f(s_i|\beta_\tau,\eta^2,v,\zeta,\sigma,s,v,\delta)\sim GIG\left(\frac{1}{2},\beta_j^2,\eta^2\right),$$

$$f(\sigma|\beta_\tau,\eta^2,v,\zeta,s,v,\delta)\sim GIG\left(a+\frac{3n}{2},(b+\sum_{i=1}^n\left(\frac{y_i-(x_i'\beta_\tau+\sigma v_i)^2}{2p^2v_i}\right)+v_i\right).$$

An indicator of model goodness is the Mean Squared Error (MSE) because it handles outliers well. Mean Squared Error (MSE) is a measure used to evaluate how well the model predicts the actual data. The main purpose of MSE is to measure the difference between the value predicted by the model and the true (or target) value in a form that is easy to calculate and understand. The objectives of MSE include measuring Model Accuracy. MSE gives an indication of how close the model prediction is to the true value. The smaller the MSE value, the better the model is at making predictions and minimizing error. In the context of model training, we strive to minimize the MSE.

This process is known as model optimization. A good model will have a lower MSE, which means that the model's predictions are closer to the true values. Avoiding Overfitting and underfitting using MSE, we can evaluate whether our model is complex enough (overfitting) or too simple (underfitting). Too high MSE on training or testing data may indicate a problem in the model. Evaluation in Regression uses MSE, which is often used in regression problems, where the goal is to predict a continuous value. MSE measures the average square of the difference between the predicted value and the true value. It provides a larger penalty for predictions that are further away from the true value. MSE measures the average squared difference between the value predicted by the model and the true value (observed value) below [26],[31]:

$$MSE=\frac{1}{n}\sum_{i=1}^n(y_i-\hat{y}_i)^2 \tag{14}$$

Where y_i is the value of the *i*-th data actual and $\hat{y_i}$ is the estimated value of the *i*-th prediction value from the model. Thus, the goal of MSE is to provide a clear and objective metric for evaluating and optimizing prediction models in various data analysis applications. So, the indicator of model goodness chosen in this study is MSE.

3. RESULTS AND DISCUSSION

3.1 Data Set

Research data sourced from the Central Bureau of Statistics of West Sumatra. Variables that are assumed to affect the poverty line (Y) are Percapita Spending (X_1), Gross Regional Domestic Product (X_2), Human Development Index (X_3), Open Unemployment Rate (X_4), and minimum wages (X_5). The data used 133 poverty lines from 2017 to 2023. Variable information can be seen in the following **Table 1** below:

Table 1. Variable Research, Description, Unit, and Type Data

Variable	Description	Unit	Type Data
Y	Poverty Line	Rupiah/Capita/month	Numeric
X_1	Percapita Spending	Thousand Rupiah/Person/Year	Numeric
X_2	Gross Regional Domestic Product	Rupiah (IDR)	Numeric
X_3	Human Development Index	Percent (%)	Numeric
X_4	Open Unemployment Rate	Percent (%)	Numeric
X_5	Minimum Wages	Rupiah	Numeric

3.2 Estimated Parameter Model of Bayesian Quantile Regression and Bayesian LASSO Quantile Regression Method.

To estimate the parameters using Bayesian Quantile Regression (BQR) and Bayesian LASSO Quantile Regression (BLQR) method, the Gibbs Sampling Monte Carlo Markov Chain (MCMC) algorithm is used. In this stage, parameter estimation will be performed with 5000 iterations and 1000 burn-ins, as can be seen in **Table 2** below. Before running iterations using MCMC, we first determine the quantile that we will choose. In this study, we use τ =0.05, τ =0.25, τ =0.5, τ =0.75, and τ =0.95. The quantiles chosen already represent the location of the data we use, namely the low quantile, the middle quantile (median), and the upper quantile. Estimation parameter uses the Software R. The parameter to be estimated is the mean of the posterior distribution. The results of parameter estimation for each quantile can be seen in **Table 2** below:

Table 2. Estimated Parameter Model BQR and BLQR

Independent Variable	BQR		BLQR	
	Estimated Mean $(\widehat{\beta})$	Width (95%)	Estimated Mean $(\widehat{\beta})$	Width (95%)
		τ =0.05		
Intercept	-278554*	169009	187777*	7589
X_1 (Percapita Spending)	25.231*	7.741	-162*	15.640
X_2 (Gross Regional Domestic Product)	0.0009*	0.5583	0.158*	10.471
X_3 (Human Development Index)	-441.3	905	24400*	566.58
X_4 (Open Unemployment Rate)	-3623*	5356.44	61500*	11201.29
X_5 (Minimum Wages)	0.1937*	0.0414	2.930*	0.1442
		$\tau = 0.25$		
Intercept	-233635*	213578	113000*	10222.575
X_1 (Percapita Spending)	24.013*	13.987	-12.700*	26.620
X_2 (Gross Regional Domestic Product)	0.0013*	0.5577	0.0831*	14.043
X_3 (Human Development Index)	-122.622	122	619.000*	117.88
X_4 (Open Unemployment Rate)	-4286*	7120.19	2810*	13526

Independent Variable	BQR		BLQR	
	Estimated Mean ($\bar{\beta}$)	Width (95%)	Estimated Mean ($\bar{\beta}$)	Width (95%)
X_5 (Minimum Wages)	0.1783*	0.3469	2.430*	11.696
$\tau = 0.50$				
Intercept	-355055*	250594	-502000*	11010
X_1 (Percapita Spending)	15.954*	13.73	-860.000*	28.565
X_2 (Gross Regional Domestic Product)	0.0001*	0.7205	0.0345*	2.3135
X_3 (Human Development Index)	3122.86*	5054.68	71800*	28305
X_4 (Open Unemployment Rate)	-3615.8	7264.32	174.000*	12985
X_5 (Minimum Wages)	0.1745*	0.042	1.850*	10.628
τ =0.75				
Intercept	-459687*	203998	116000*	10606.92
X_1 (Percapita Spending)	5.349	1.0226	-527*	21.027
X_2 (Gross Regional Domestic Product)	0.0013*	0.7921	0.018*	1.434
X_3 (Human Development Index)	6129.49*	4224	58500*	23355
X_4 (Open Unemployment Rate)	-3879	7309.45	-8820*	14185.20
X_5 (Minimum Wages)	0.1844*	0.0379	1.430*	8.782
$\tau = 0.95$				
Intercept	-429149*	191066	-373000*	10179
X_1 (Percapita Spending)	2.8166	5.220	-242*	5.891
X_2(Gross Regional Domestic Product)	0.0040*	0.543	0.024*	2.5392
X_3 (Human Development Index)	5792*	4285	6860*	22412
X_4 (Open Unemployment Rate)	-95.823	554	-156*	831.34
X_5 (Minimum Wages)	0.1935*	0.0336	0.908*	8.894
***Significant at $\alpha = 0.05$**				

Based on **Table 2**, it is known that the use of the BLQR method obtained different significance results for the independent variables in each quantile, and the BQR method was not significant for all quantiles. The BLQR method obtained all the variables as statistically significant in influencing the poverty line in all quantiles. But in BQR, the Human Development Index (X_3) not statistically significant in influencing poverty line in quantiles 0.05 and 0.25, and open unemployment Rate (X_4) not statistically significant in influencing the poverty line in quantiles 0.75 and 0.90. The Bayesian quantile regression method has the value of MSE for all quantiles, it can be seen in **Table 3** below:

Table 3. MSE Value BQR and BLQR

Quantile	Model BQR	Model BLQR
	MSE	MSE
0.05	0.586	0.348
0.25	0.383	0.263
0.5	**0.217**	**0.208**
0.75	0.391	0.295
0.90	0.445	0.38

In **Table 3** above, it can be seen that for each quantile, the Bayesian LASSO quantile regression method (BLQR) has the smallest MSE value in quantile 0.5 of 0.208. So the best model chosen is:

$$\hat{y} = -502000 - 860X_1 + 0.0345X_2 + 71800X_3 + 174X_4 + 1.850X_5 \quad (15)$$

Based on **Equation (15)**, the best model obtained, it can be interpreted that an increase in per capita income of one thousand rupiah/person/year will reduce the poverty line by 860 Rupiah/capita/month. If Gross Regional Domestic Product increases by one rupiah, then the poverty line will increase by 0.034 thousand/capita/day. If the Human Development Index increases by one percent, it will increase the poverty line by 71800 Rupiah/capita/day. If the Open Unemployment Rate increases by one percent, it will increase the poverty line by 174 Rupiah/capita/day. If the Minimum wage increases by one Rupiah, then the poverty line will increase by 1.850 thousand/capita/day. Furthermore, it is necessary to perform a convergence test for each model parameter resulting from applying the BLQR method. The convergence test is identified by looking at the results of the trace plot and the density plot. The results of the convergence test are presented in **Figure 1** below:

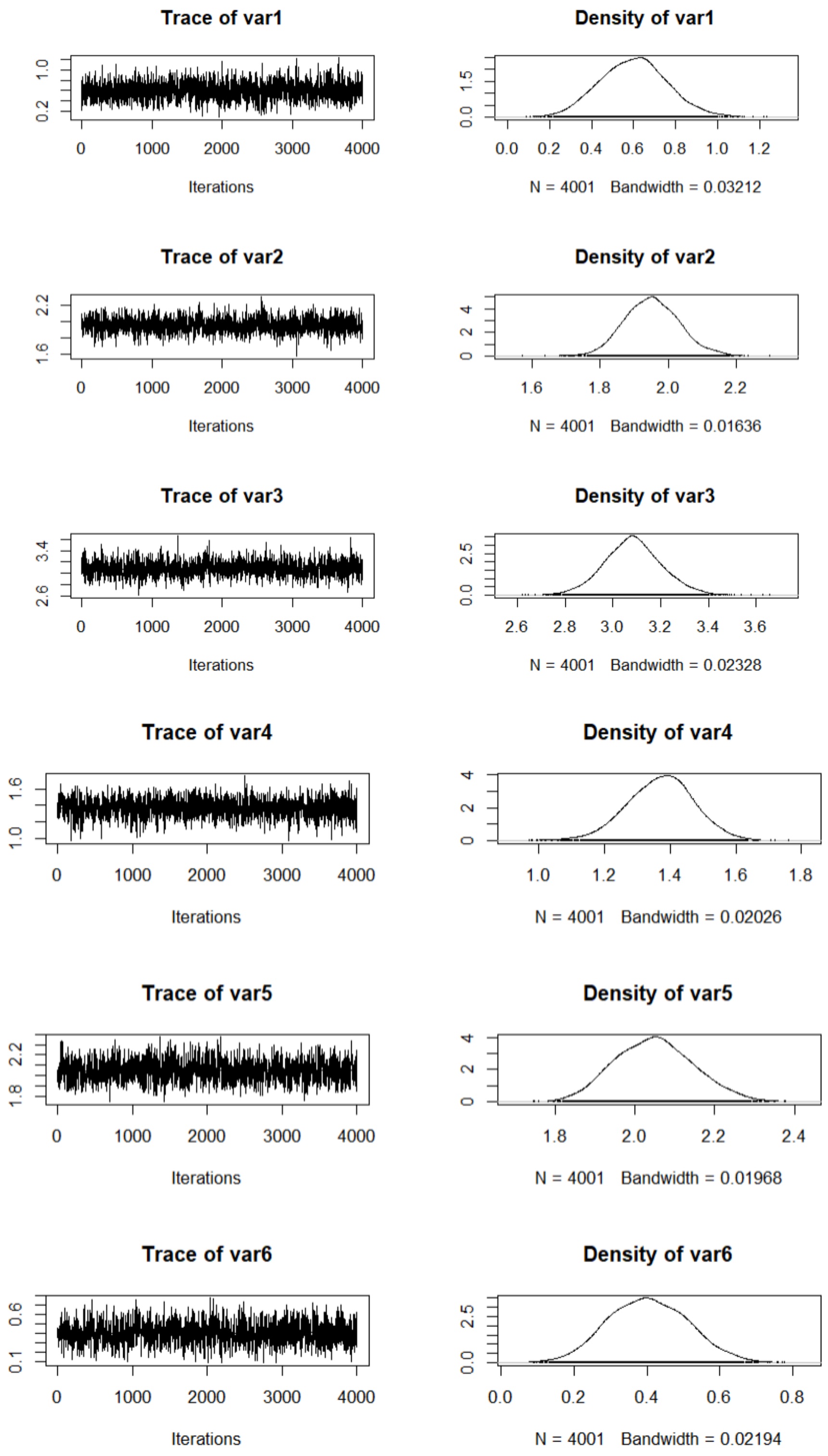

Figure 1. Trace Plot and Density Plot of all Parameters for $\tau = 0.5$

From **Figure 1**, the resulting trace plot has formed two horizontal linear lines for each parameter. Thus, it is said that the estimated values of the model parameters have converged to a certain value. **Figure 1** also shows that the density plot produced for each parameter estimate already resembles a normal distribution curve, which is symmetrical, meaning that the estimated model parameter values are normally distributed.

4. CONCLUSIONS

In this paper, we have presented a Bayesian approach for quantile regression dan Bayesian LASSO quantile regression. The advantages of this approach are, first, that it compares two methods; the estimation and variable selection procedure is insensitive with regard to outliers, heteroskedasticity, or other anomalies that can break existing methods down. And second, the selection of predictive variables affecting the dependent variable without sensitivity to abnormal values, unlike other methods such as the method of ordinary least squares. A Bayesian approach to this problem is to put a Laplace prior distribution on the regression parameters. The Bayesian LASSO quantile regression method (BLQR) using the MCMC Gibbs Sampling algorithm is proven to be easier and more practical to apply and produces better estimators than estimators produced by ordinary quantile regression. From the case study described above, the best model is obtained at quantile 0.50, because it has a small MSE value of 0.208**.** The independent variables that significantly affect the poverty line are minimum wage, gross regional domestic product and per capita spending, Open Unemployment Rate, and Human Development Index.

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