Journal of Social and Economic Statistics
Vol. 5, No. 1, Summer 2016

SOME METHODS OF QUANTILE REGRESSION FOR ANALYSIS OF THE POVERTY IN IRAQ

Fadel HAMID HADI ALHUSSEINI [a]

Abstract

World Bank has mentioned that approximately half of the world's poor people live in countries with high income and many of these countries are oil producer countries. In this paper we study some of the economic variables (unemployment, average monthly per capita income, average monthly per capita spending on basic food, the rise in prices of these basic food goods and average taxes imposed on the Iraqi citizen) that impact on the increasing number of poor households in Iraq. We employ a regression model based on classical quantile regression for building the models which represent the relationship between the response variable and the covariates, through five quantile lines (0.16, 0.33, 0.50, 0.66, 0.83). We also use Bayes Lasso quantile regression for variable selection. The data were taken from an economic survey made by the Central Bureau of Statistics in 2007. We use R packages quantreg and bayesQR.

Keywords: poverty line, quantile regression model, Bayesian Lasso quantile regression, average number of poor Iraqi households

JEL Classification: C11, C51, C52, C88

Author's Affiliation

[a] - Department of Statistics and Informatics, University of Craiova, email:fadhelfadhel222@yahoo.com

1. Introduction

World Bank has defined as countries with low income the countries in which the individual income is about 600$ per year. Most of these countries are in Africa, including 15 countries with average individual income of less than 300$ per year. About 45% of the world's poor people live in countries with high income. During the second half of the twentieth century, there was much talking about poverty and the poor people in the literature.

There is no international agreement for defining the poverty due to the overlapping of economic, social and political factors, but there is agreement regarding the link between poverty and the degree of satisfaction of the basic needs. There is also an agreement about the concept of poverty as a state of physical deprivation which can be translated in insufficient food consumption (both in quantity and quality), poor health status, educational level and residential status. This reflects the economic status in which the individual does not gain sufficient income to get the minimum levels of health care, food, clothing, education and all the necessary requirements for ensuring an appropriate quality of life.

Some studies and researches have tried to establish specific classifications for the phenomenon of poverty by dividing it into several types, such as:

-Absolute Poverty is the situation in which the income cannot satisfy basic needs represented by food, housing, clothing, education, health and transportation.

-Extreme Poverty (Disruptive Poverty) is the situation where the human cannot satisfy his food needs by getting enough calories to enable him to continue his live.

-Welfare Poverty is a kind of poverty encountered especially in the Western societies, in which some individuals don’t have access to modern scientific achievements as advanced equipment and some diverse entertainment.

The World Bank mentioned that approximately half of the world's poor people live in countries with high income and some of these countries are oil producers, including Iraq. Reports show that the number of poor people in Iraq is more than 11 million and poverty percentage in Iraq is 23%, approximately a quarter of its population. The poor families in Iraq are affected by severe unemployment with an average of unemployment for adults (15 years and older) reaching 19% among poor households. The monthly average per capita income for poor households is about 45 thousand dinars, or the equivalent of 30 $ per monthly or 1 $ per day. Average monthly spending per capita on basic food goods does not exceed 90 000 dinars, which is equivalent of 75 $ monthly. The rising prices of basic food goods and high taxes imposed on the Iraqi citizen contribute in increasing average number of poor Iraqis households.

In this paper we aim to study and analyze the importance of these factors affecting the increase of poor households in Iraq and also choose the most important variables which affect the rate of increase in the number of poor households in Iraq, through regression quantile analysis. The rest of this paper is organized as follows. In section 2 we explain the method of quantile regression, first quantile regression model, second Bayesian Lasso quantile regression. In section 3, we employ these regression methods on a sample data and in section 4, we present a brief conclusion.

2. Methods of Quantile Regression

We use two methods of quantile regression analysis to explain the variables affecting the number of poor households in Iraqi population.

2.1. Quantile Regression Method

The key idea of the regression analysis it is to evaluate the relationship between a response variable and set of explanatory variables, via the following model:

$$y_i = x_i^T \beta + u_i \ , \qquad (1)$$

where,

y_i it is response variable

β: it are parameters of model,

x_i^T : set of explanatory variables,

u_i is random variable term, $u_i \sim N(0, \sigma^2)$

The model (1) focus is to estimate the conditional mean of response variable, $E(y_i|x_i)$, where:

$$E(y_i|x_i) = E(x_i^T \beta + u_i) = x_i^T \beta \qquad (2).$$

The accuracy of regression parameters is restricted by a set of assumptions and in case of violating one of these assumptions we get inaccurate estimators for regression parameters. Therefore conditional mean for the dependent variable works under a set of assumptions. One of these assumptions is that the random error term is distributed according to a normal distribution. Such assumptions are not important in quantile regression model, which was introduced by Koenker and Bassett (1978).

Quantile regression model is considered as a normal extension to classical regression model. It can estimate parameters accurately even if the above assumptions are not achieved. The quantile regression model provides a great flexibility in estimating its parameters, and it is not affected by the existence of outlier values. Chernozhukov and Hansen (2008)) mention that the quantile regression is robust against outlier values. Also quantile regression model can estimate its parameters even if the distribution of the random error term is asymmetric. This means the random error in quantile regression is distribution free. Also quantile regression model provides full coverage for each data of response variable, through the estimation of a set of quantile lines at any position of the distribution of response variable.

Thus, quantile regression model takes the following form:

$$y_i = x_i^T \beta_\theta + u_{i_\theta} \quad , \tag{3}$$

$$Q_\theta(y_i|x_i) = x_i^T \beta_\theta + F^{-1}(u_i) = x_i^T \beta_{\theta + Q_\theta(u_i)} = x_i^T \beta_\theta \; , \tag{4}$$

where $Q_{\theta_{ui}} \equiv F^{-1}(u_i)$ $\quad and \;\; \theta_{th}$ is the value of quantile proportion

$$0 < \theta_{th} < 1. \qquad 0 < \theta_1 < \theta_2 < \theta_3 \;\dots\dots\dots < \theta_n < 1.$$

Therefore, quantile regression lines depend on the natural of the data under study. For example, if the aim of the study is raising diabetes, then the better quantile regression line passes at grouping rising diabetes data. If the aim of the study is to study the low diabetes, then better quantile regression line passes at grouping low diabetes data. Therefore quantile regression model has flexibility in representing the phenomena. As in the following figure:

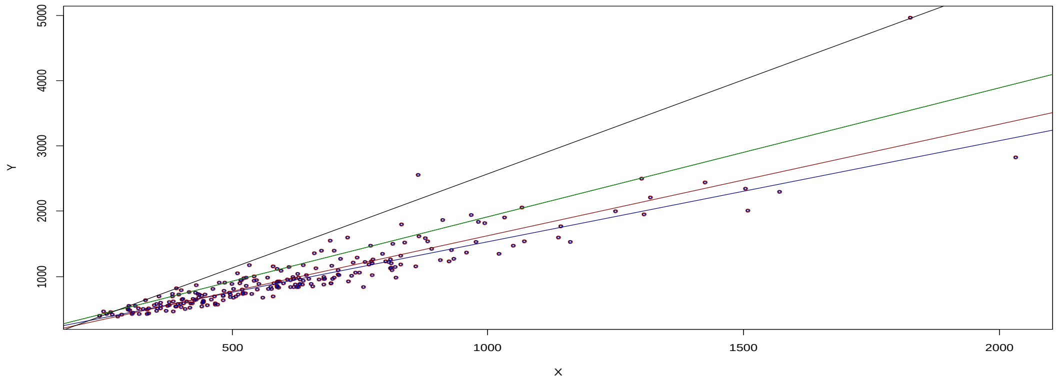

Figure 1: The set of lines for quantile regression model

In this case we will get a set of quantile regression models at each specific proportion from quantile proportion according to the following:

$$Q_{\theta_1}(T_i|x_i) = \alpha_{\theta_1} + x_i^T\beta_{\theta_1} \quad if\ \theta_1 = 0.25\ then\ the\ model\ Q_{0.25}(T_i|x_i) = \alpha_{0.25} + x_i^T\beta_{0.25},$$

$$Q_{\theta_2}(T_i|x_i) = \alpha_{\theta_2} + x_i^T\beta_{\theta_2} \quad if\ \theta_2 = 0.50\ then\ the\ model\ Q_{0.50}(T_i|x_i) = \alpha_{0.50} + x_i^T\beta_{0.50},$$

$$Q_{\theta_3}(T_i|x_i) = \alpha_{\theta_3} + x_i^T\beta_{\theta_3} \quad if\ \theta_3 = 0.80\ then\ the\ model\ Q_{0.80}(T_i|x_i) = \alpha_{0.80} + x_i^T\beta_{0.90},$$

$$Q_{\theta_4}(T_i|x_i) = \alpha_{\theta_4} + x_i^T\beta_{\theta_4} \quad if\ \theta_4 = 0.95\ then\ the\ model\ Q_{0.95}(T_i|x_i) = \alpha_{0.95} + x_i^T\beta_{0.95},$$

In order to estimate the parameters of the quantile regression model, we have to minimize the following equation:

$$\underset{\beta_\theta}{Min} \sum \rho_\theta \,|(y_i - (x_i^T\beta_\theta)| \qquad (5),$$

where $\rho_k(u_{i)}$ is called loss function..

$$\rho_k(u_{i)} \begin{cases} (\theta)|(y_i - (x_i^T\beta_\theta))| & y_i \geq (x_i^T\beta_\theta) \\ -(1-\theta)|(y_i - (x_i^T\beta_\theta))| & y_i < (x_i^T\beta_\theta) \end{cases}$$

Equation (5) is looking for weighted deviations between real values and predictive values $(y_i - \hat{y}_i)$. From above formula positive residuals take weight θ and negative residuals take weight $(1-\theta)$.

It is possible to estimate the parameters for quantile regression model through the following formula:

$$\sum d_\theta\,(y_i, \hat{y}_i) = \theta \sum_{y_i \geq x_i^T\beta_\theta} |y_i - x_i^T\beta_\theta| + (1-\theta) \sum_{y_i < x_i^T\beta_\theta} |y_i - x_i^T\beta_\theta| \qquad (6)$$

where d_θ is the distance between values observation and quantile regression line. In equation (6) the first part represents the vertical distance above quantile regression line, which takes the weight θ and second part represents the vertical distance under quantile regression line, which takes weight $1-\theta$.

Since (6) is not differentiable at the origin, there is no exact solution for it (Koenker, 2005) and the minimization of (6) can be achieved by a linear programming algorithm (Koenker and D'Orey, 1987) or by use of *Bootstrapping* (Mooney, 1993). In order to estimate the parameters of quantile regression model we will use the Bootstrapping method, as it exists in "quantreg" package.

2.2. Bayesian Lasso Analysis Quantile Regression

Regression models constructing depends on independent variables. Likewise, quantile regression model constructing depends on a set of independent variables which have variety effects. Maybe some of these variables are not useful in constructing the model, maybe weaken the predicting ability of the model. Thus excluding these non-important variables of quantile regression model the predictive accuracy may be improved. There are many statistical methods for variable selection that inters in building regression models, such as Akaike information criteria (AIC) method proposed by Akaike (1973) and Bayesian information criteria (BIC) method proposed by Schwarz (1978), but the above mentioned methods are traditional and poor methods, because they need a long time to achieve variables selection.

Tibshirani (1996) proposed the Lasso method (least absolute shrinkage and selection operator), which differs from previous methods. Lasso can estimate and select variables in same time, also achieving estimation accuracy for model parameters. The Lasso method focus on selection of variables that have parameter values far from zero (in case positive or negative) and exclude variables for which the parameter values are exactly equal to zero or very close to it. The Lasso method plays a special role in constructing quantile regression models.

Koenker (2004)) is the first researcher to employ Lasso method in quantile regression model for the variables selection, building quantile regression model through following equation:

$$\underset{\alpha_\theta,\beta_\theta}{Min} \sum \rho_\theta \, |(y_i - (x_i^T \beta_\theta)| + \lambda \sum_{j=1}^{k} |\beta_{\theta j}| \qquad (7).$$

where quantity $\lambda \sum_{j=1}^{k} |\beta_{\theta j}|$, is called penalty term for estimate of parameters quantile regression model. Yu and Moyeed (2001) proposed a Bayesian formulation of QR employing the Skewed Laplace distribution (SLD) for the errors. It is function of a random error distribution for quantile regression, $i = 1,2,\ldots\ldots,n$ u_i as below shown.

$$f(u|\theta) = \theta(1-\theta)exp\{-\rho_\theta(u)\}. \qquad (8)$$

And the joint function for distribution response variable takes the following shape:

$$f(y|,x,\beta_\theta,\alpha_\theta,\theta) = \theta^n(1-\theta)^n exp\left\{-\sum_{i=1}^{n}\rho_\theta(y_i-(x_i^T\beta_\theta)\right\} \quad (9),$$

If we assume the prior distribution of the parameter vector β_θ symmetric Laplace distribution

$$g(\beta_\theta|\lambda) = (\lambda/_2)^k \exp\left(-\lambda\sum_{j=1}^{k}|\beta_{\theta j}|\right) \qquad (10)$$

posterior distribution for parameters quantile regression model takes the following shape:

$$p(\beta_\theta|,y,x,\lambda,\alpha_\theta) =\propto \exp-\left\{\sum_{1=1}^{n}\rho_\theta(y_i-(x_i^T\beta_\theta)\right\}-\sum_{j=1}^{k}|\beta_{\theta j}| \qquad (11)$$

We minimize equation (7) or equivalently maximize equation (11). For facilitating the solution we will rewrite equation (9) in another way, according Kozumi and Kabayshi (2011), through reformulation of the error term which follows a Skewed Laplace distribution mixture between two distributions, standard exponential and standard normal models, so the error model is:

$$u = \varphi z + \tau\sqrt{z}\epsilon \quad , \qquad (12)$$

where $z\sim \exp(1)$ $\quad and \quad \epsilon\sim N(0,1)$

$$E(u) = \varphi E(z) + \tau\sqrt{E(z)\,E(\epsilon)}$$

$$E(u) = \varphi \quad then\ \varphi = \frac{1-2\theta}{\theta(1-\theta)}$$

$$var(u) = \varphi^2 var(z) + \tau^2\sqrt{var(z)}\ var(\epsilon)$$

$$\frac{1-2\theta+2\theta^2}{\theta^2(1-\theta)^2} = \frac{(1-2\theta)^2}{\theta^2(1-\theta)^2} + \tau^2$$

$$\tau^2 = \frac{1 - 2\theta + 2\theta^2}{\theta^2(1-\theta)^2} - \frac{1 - 4\theta + 4\theta^2}{\theta^2(1-\theta)^2}$$

$$\tau^2 = \frac{1 - 2\theta + 2\theta^2 - 1 + 4\theta - 4\theta^2}{\theta^2(1-\theta)^2}$$

$$\tau^2 = \frac{2\theta - 2\theta^2}{\theta^2(1-\theta)^2} = \frac{2\theta(1-\theta)}{\theta^2(1-\theta)^2} = \frac{2}{\theta(1-\theta)}$$

$$y_i = x_i^T \beta_\theta + \varphi z_i + \tau\sqrt{z_i}\epsilon_i \qquad (13)$$

$$y_i \sim N(x_i^T \beta_\theta + \varphi z_i, \tau^2 z_i)$$

In this case the joint density of y was:

$$f(y|\alpha_\theta, \beta_{\theta, z_i}) \propto \left(\prod_{i=1}^{n} z_i^{\frac{-1}{2}}\right) \exp - \left\{\sum_{1=1}^{n} \frac{(y_i - x_i^T \beta_\theta - \varphi z_i)^2}{2\tau^2 z_i}\right\} \qquad (14)$$

The equation (14) is another formula for asymmetric Laplace distribution according to Kozumi and Kabayshi (2011)). Qing Li et al. (2010) use Bayes method for estimating the parameters and variable selection for quantile regression model including Lasso method. Parameter estimating by using Bayesian Lasso quantile regression is achieved through special software packages ("bayesQR").

3. The Sample and Data Analysis

We use the economic survey made by the Central Bureau of Statistics in 2007. The sample size under study was 56 observations divided to three locations for each governorate except Baghdad capital, we have chosen five location.

The variables of this sample are:

Y: Average number of poor Iraqi households.

.X_1: Unemployment Average.

.X_2: Average Monthly per capita income.

.X_3: Average spending monthly per capita on basic food.

.X_4: The rise in prices of these basic food goods.

.X_5: Average taxes imposed.

The study and analysis of the effect of these five variables on average number of poor Iraqi households is possible through using some methods of quantile regression.

We use R programming, which is free software, namely the packages (quantreg) and (bayesQR).

3.1 Data Analysis

We assume that the quantile regression lines in this paper are five. The quantile proportion for these five lines can be determined as follows.

$$\theta_q = \frac{q}{Q+1} for\ q = 1, \dots, Q.$$

Thus the quantile proportion is :

$$\theta_1 = \frac{1}{Q+1} = \frac{1}{6} = 0.16,\ \theta_2 = \frac{2}{6} = 0.33,\ \theta_3 = \frac{3}{6} = 0.50,\ \theta_4 = \frac{4}{6} = 0.66,\ \theta_5 = \frac{5}{6} = 0.83$$

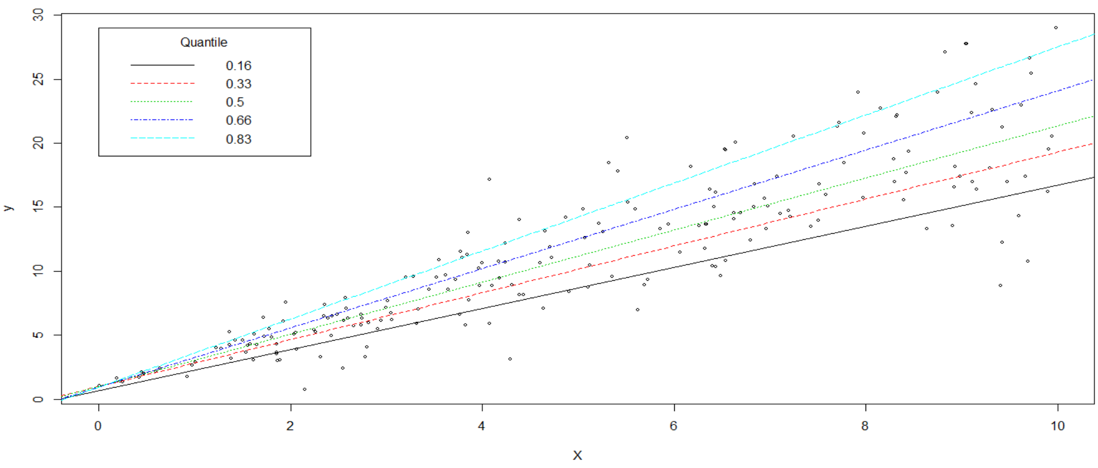

Figure 2: Quantile lines according to quantile proportion

For analysing the sample data we depend on two methods.

3.1.1. Quantile Regression Model

The quantile regression model computes each regression line separately. Each quantile regression model differs based on quantile proportion.

Table 1 at quantile proportion (0.16): the pseudo-R squared = 0.1565394 means that the independent variables (Unemployment Average, average Monthly per capita income, Average spending monthly per capita on basic food, The Rising prices of these basic food goods, average taxes imposed) explain 15.65% from the variation in average number of poor Iraqi households. This indicator shows weakness of quantile regression model at quantile proportion (0.16) in representation of the data. At quantile proportion (0.16) one variable (Unemployment Average) has significant effect on average number of poor Iraqi households and the rest variables are non-significant.

Table 1: Results of quantile regression model according quantile proportions (0.16,0.33,0.50,0.66,0.83)

Quantile proportion	Variables	Coefficients	Std. Error	t value	Pr(>|t|)	The pseudo-R squared
$\theta_1 = (0.16)$	Intercept	-41703.97	67606.79	-0.61686	0.54013	0.1565394
	X_1	1.76225	0.38460	4.58203	**0.00003**	
	X_2	-0.26854	0.31888	-0.84213	0.45373	
	X_3	0.87725	0.75827	1.15690	0.45281	
	X_4	-0.05189	0.33199	-0.15631	0.87642	
	X_5	-0.28789	0.46001	-0.62583	0.53427	
$\theta_2 = (0.33)$	Intercept	-50568.71	55422.69	-0.9124	0.36593	0.3897516
	X_1	1.84098	0.33182	5.54811	**0.00000**	
	X_2	0.23653	0.22575	1.04778	0.29978	
	X_3	0.88825	0.61245	1.45033	0.15321	
	X_4	-0.00585	0.30630	-0.01911	0.98483	
	X_5	-0.14407	0.41788	-0.34477	0.73172	
$\theta_3 = (0.50)$	Intercept	-2844.18516	64797.98859	-0.04389	0.96516	0.4705203
	X_1	1.85200	0.42666	4.34073	**0.00007**	
	X_2	0.34970	0.23762	1.47169	0.14737	
	X_3	0.26405	0.56637	0.46622	0.64308	
	X_4	0.08169	0.34319	0.23803	0.81283	
	X_5	-0.49718	0.40735	-1.22051	0.22800	
	Intercept	24623.70637	61498.47814	0.40040	0.69057	0.6484423
	X_1	1.66437	0.48729	3.41559	**0.00127**	
	X_2	0.27056	0.26910	1.00543	0.81953	

$\theta_4 = (0.66)$	X_3	-0.02400	0.53759	-0.04464	0.96457	
	X_4	-0.14579	0.38908	-0.37470	0.09947	
	X_5	0.49837	0.38213	1.30417	**0.03815**	
$\theta_5 = (0.83)$	Intercept	115811.49775	52740.84578	2.19586	0.63277	**0.815514**
	X_1	1.43121	0.43062	3.32362	**0.00167**	
	X_2	-0.16574	0.27736	0.59756 -	**0.00283**	
	X_3	0.21400	0.73603	0.29075	**0.01245**	
	X_4	0.43544-	0.39880	1.09188-	0.6222	
	X_5	0.19240	0.39251	0.49019	0.6261	

Table 1 at quantile proportion (0.33): the pseudo-R squared =0.3897516 means that the independent variables (Unemployment Average, average Monthly per capita income, Average spending monthly per capita on basic food, The Rising prices of these basic food goods, average taxes imposed) explain 38.97% from the variation in average number of poor Iraqi households. This indicator shows weakness quantile regression model at quantile proportion (0.33) in representation of the data. At quantile proportion (0.33) there is one variable (Unemployment Average) with significant effect and the rest variables are non-significant.

Table 1 at quantile proportion (0.50): the pseudo-R squared =**0.**4705203 means that the independent variables (Unemployment Average, average Monthly per capita income, Average spending monthly per capita on basic food, The Rising prices of these basic food goods, average taxes imposed) explain (47.05%) of the variation. This indicator shows weakness quantile regression model at quantile proportion (0.50) in representation of the data. At quantile proportion (0.50) there is one significant variable (Unemployment Average).

Table 1 at quantile proportion (0.66): the pseudo-R squared = 0.6484423 means that the independent variables explain (64.84%) from the variation. This indicator shows strength quantile regression model almost at quantile proportion (0.66) in representation of studied phenomenon data. At quantile proportion (0.66) there are two variables (Unemployment Average and average taxes imposed) with significant effect and the rest variables are non-significant.

Table 1 at quantile proportion (0.83): the pseudo-R squared = 0.815514 means that independent variables explain 81.55% from the variation. This indicator shows strength quantile regression model almost at quantile proportion (0.83) in representation of studied phenomenon data.

We can conclude that the best quantile regression line is quantile proportion (0.83). Thus we will focus in explaining it. At quantile proportion (0.83) there are three variables

(Unemployment Average, average Monthly per capita income, average Spending monthly per capita on basic food) with significant effects.

The relationship between Unemployment Average and average number of poor Iraqi households is positive: if Unemployment Average increases by one unit it leads to an increase of 1.43121 in the average number of poor Iraqi households. The relationship between average Monthly per capita income and average number of poor Iraqi households is negative. This means that if the average Monthly per capita income decreased by one unit this leads to the increase of average number of poor Iraqi households by 0.16574.

The relationship between average Monthly per capita spending on basic food and the average number of poor Iraqi households is positive: if there is an increase in average monthly per capita income with one unit, this will lead to an increase in the average number of poor Iraqi households by 0.21400. Through the results displayed for the above three variables are in accordance with the economic logic.

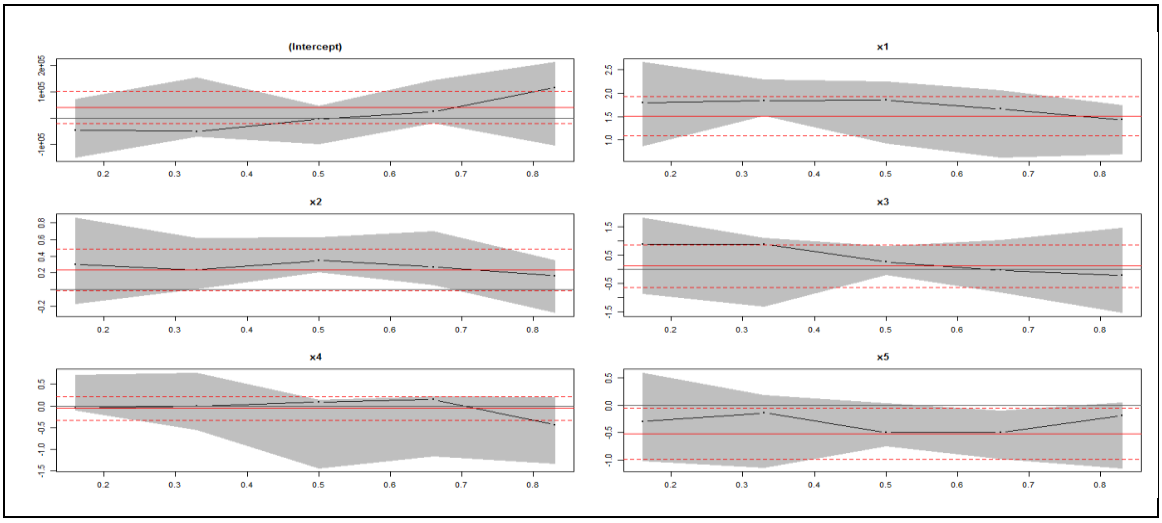

Figure 3: Estimate of the variables' coefficients through five proportion quantiles

3.1.2 Method of Bayesian Lasso Quantile Regression

According to Table 2 at quantile proportions (0.16) we find most of the variables have direct effect on average number of poor Iraqi households, except [x4] (The Rising prices of these basic food goods). This variable is not important because its value is close to zero (-0.0795). But we find that variable [x1] (Unemployment) is far from zero (1.7914). If we compare it with other variables this means that variable [x1] (Unemployment) has more effect on average number of poor Iraqi households.

Table (2) at quantile proportion (0.33): we find that variable [X1] (Unemployment Average) is the most important variable and variable [X4] (The Rising prices of these basic food goods) is a weak variable in building quantile regression model at proportion (0.33).

Table 2 at quantile proportion (0.50): the results do not differ much from previous results of quantile proportion since the variable [x1] (Unemployment Average) remained the most important and also [x4] (Rising prices of these basic food goods) is considered to be weak.

Table 2 at quantile proportion (0.66) also does not differ much from previous quantile proportion.

Table 2 at quantile proportion (0.83) does not differ much from previous quantile proportion where the variable [x1] (Unemployment Average) is much more important. We find parameter value of this variable moved away more from zero (2.396) which shows the strength of the effect of this variable in average number of poor Iraqi households. Also at quantile proportion (0.83) we find that variable [x4] (Rising prices of these basic food goods) has a very weak effect in building quantile regression model as we find parameter value of this variable is more close to zero (-0.003). Thus we can exclude this variable from quantile regression model at quantile proportion (0.83) according to data under study.

Table 2: Results method Bayesian Lasso quantile regression according quantile proportion (0.16,0.33,0.50,0.66,0.83)

Quantile proportion	Variables	Coefficients	lower limit	upper limit
0.16	(Intercept)	-1.2019	-20.3137	18.204
	X1	1.7914	1.7914	1.799
	X2	0.2493	0.2455	0.256
	X3	0.2367	0.2277	0.242
	X4	-0.0795	-0.0802	-0.079
	X5	-0.3204	-0.3233	-0.318
0.33	(Intercept)	-33.3118	-54.1174	-13.1189
	X1	1.5792	1.5786	1.5798
	X2	0.2673	0.2659	0.2706
	X3	0.4584	0.4565	0.4593
	X4	-0.0457	-0.0459	-0.0456
	X5	0.4953	0.4981	0.4941
0.50	(Intercept)	-14.403	-33.5405	5.0893
	X1	1.831	1.8308	1.8328
	X2	0.339	0.3388	0.3396
	X3	0.296	0.2904	0.2988
	X4	0.075	0.0746	0.0756
	X5	-0.552	-0.5545	-0.5477
0.66	(Intercept)	39.325	17.531	60.997
	X1	1.719	1.717	1.720
	X2	0.291	0.291	0.291
	X3	0.180	0.178	0.183
	X4	0.147	0.146	0.147

	X5	-0.341	-0.344	-0.340
0.83	(Intercept)	29.209	9.323	50.4984
	X1	2.396	2.385	2.4084
	X2	0.416	0.413	0.4196
	X3	1.249	1.170	1.3351
	X4	-0.003	-0.070	-0.0607
	X5	-0.724	-0.760	-0.6866

In below plot parameters estimation depends on (5000) iterations.

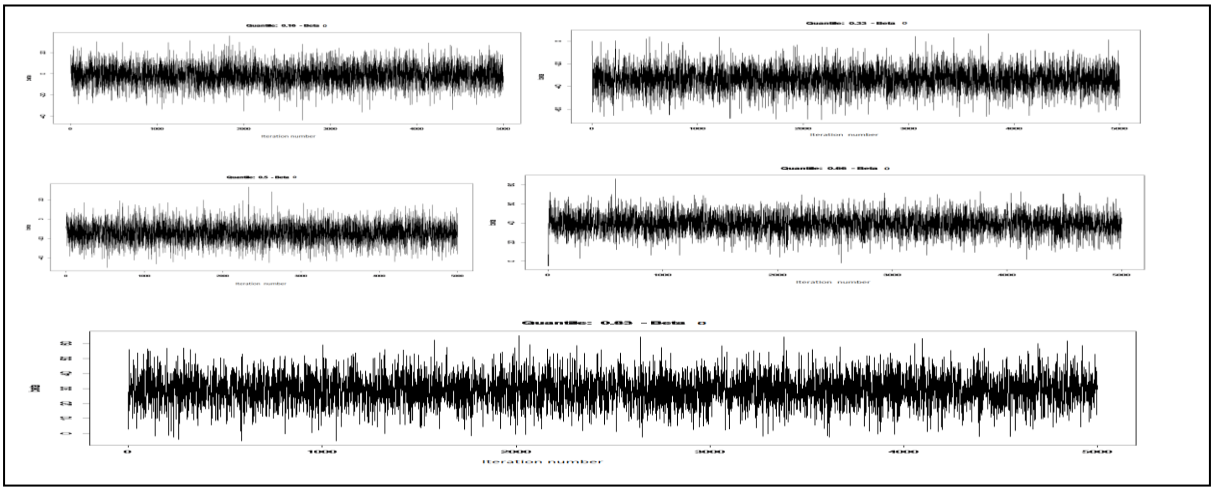

Figure 4: Plot for intercept via five quantiles and based on 5000 iteration

Figure 4 shows the intercept parameter estimates for quantile regression model at the five quantile proportion was stationary through (5000) iterations, but the gap between upper limit and lower limit for parameters estimated to intercept term was large (at credible intervals 95%) through (5000) iterations.

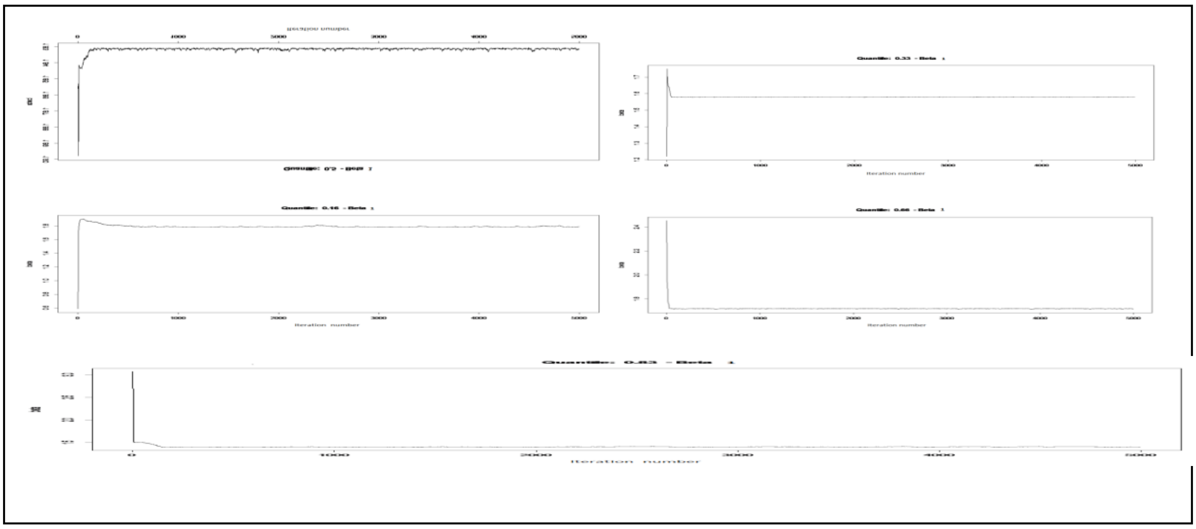

Figure 5: Plot for β_1 via five quantiles and based on 5000 iterations

Figure 5 shows the parameter estimates [β_1] {Unemployment Average} for quantile regression model at the five quantile proportion was stationary through (5000) iterations. But the gap between upper limit and lower limit for estimated parameters to [β_1] {Unemployment Average} was convergent (at credible intervals 95%) through (5000) iterations.

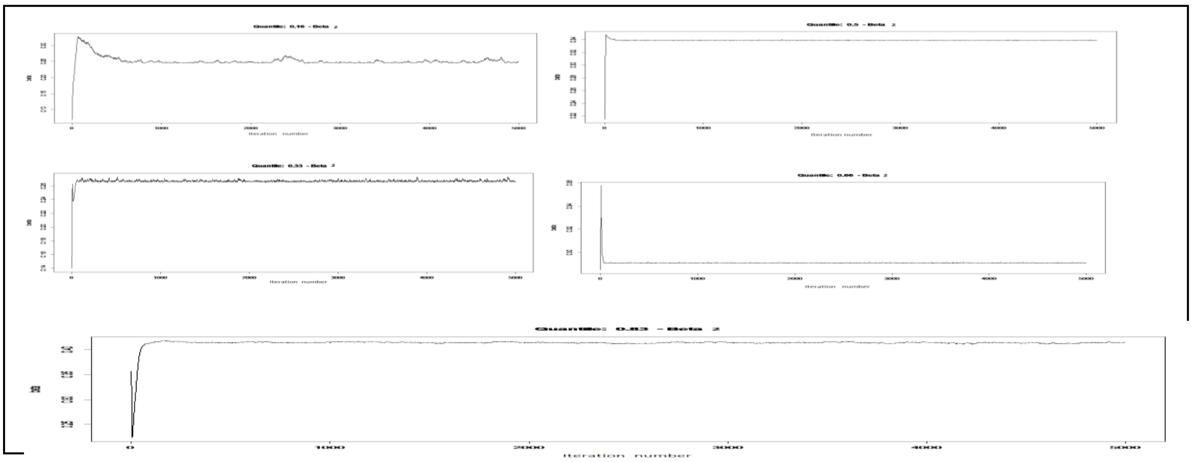

Figure 6: Plot for β_2 via five quantiles and based on 5000 iterations

Figure 6 shows that the estimates of [β_2] {average Monthly per capita income} for quantile regression model at the five quantile proportion was stationary through (5000) iterations, but the gap between upper limit and lower limit for parameters estimated the special β_2 {average Monthly per capita income} was convergent (at credible intervals 95%) through (5000) iterations.

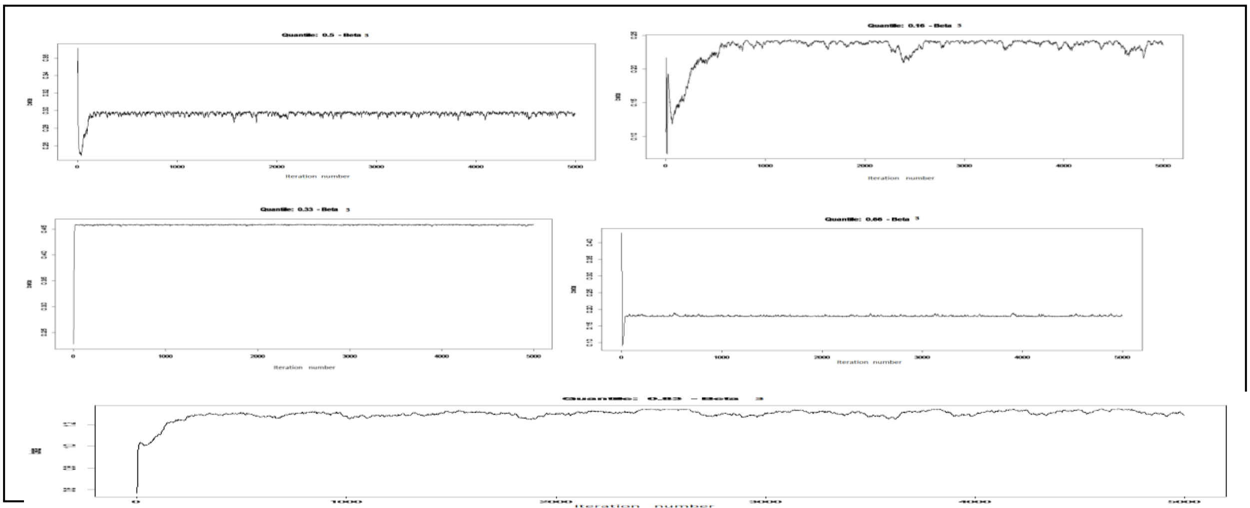

Figure 7: Plot for β_3 via five quantiles and based on 5000 iterations

Figure 7 shows that estimates of [β_3]{ Average spending monthly per capita on basic food} for quantile regression model at the five quantile proportion was not stationary at some quantile proportion through (5000) iterations, the estimates of [β_3] {Average spending monthly per capita on basic food} was non stationary at quantile proportion (0.16) but the estimates of [β_3]{Average spending monthly per capita on basic food} was stationary at other quantile proportions. The gap between upper limit and lower limit for estimated parameter [β_3]{ Average spending monthly per capita on basic food} was convergent (at credible intervals 95%) through (5000) iterations.

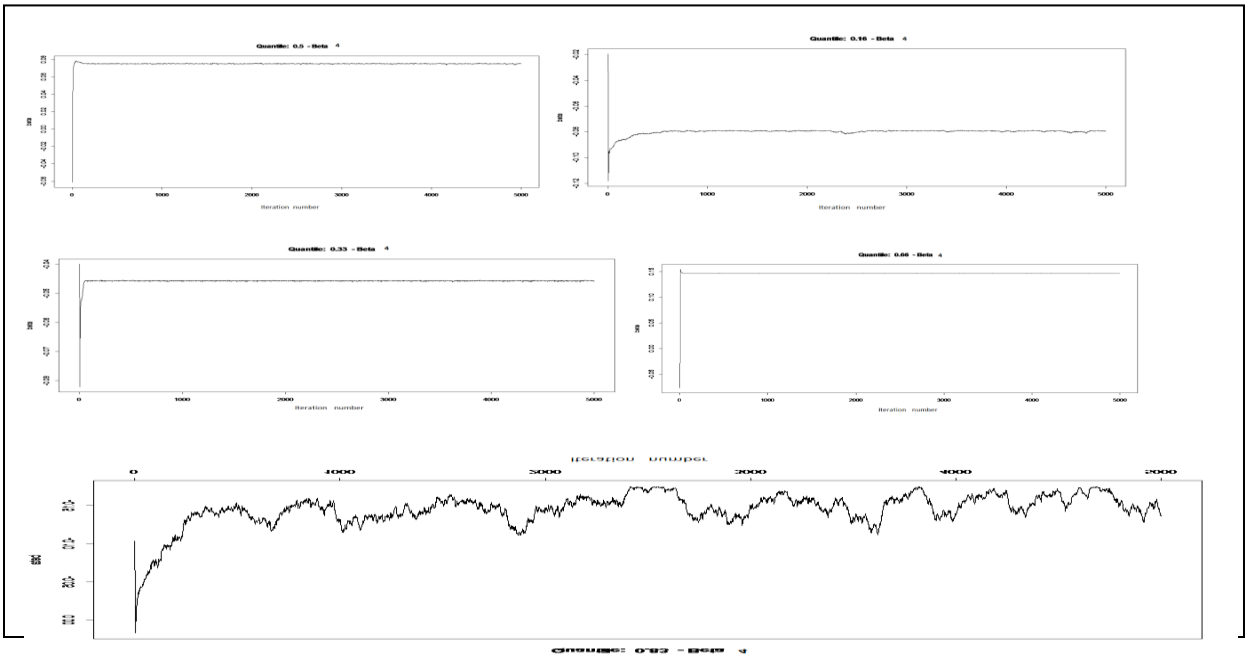

Figure 8: Plot for β_4 at five quantile and based on 5000 iterations.

Figure 8 shows that the estimate of $[\beta_4]$ {The Rising prices of these basic food goods} for quantile regression model at the five quantile proportion was not stationary at some quantile proportion through (5000) iterations, was non stationary at quantile proportion (0.83) but it was stationary at other quantile proportions. The gap between upper limit and lower limit for the estimate parameter was convergent (at credible intervals 95%) through (5000) iterations.

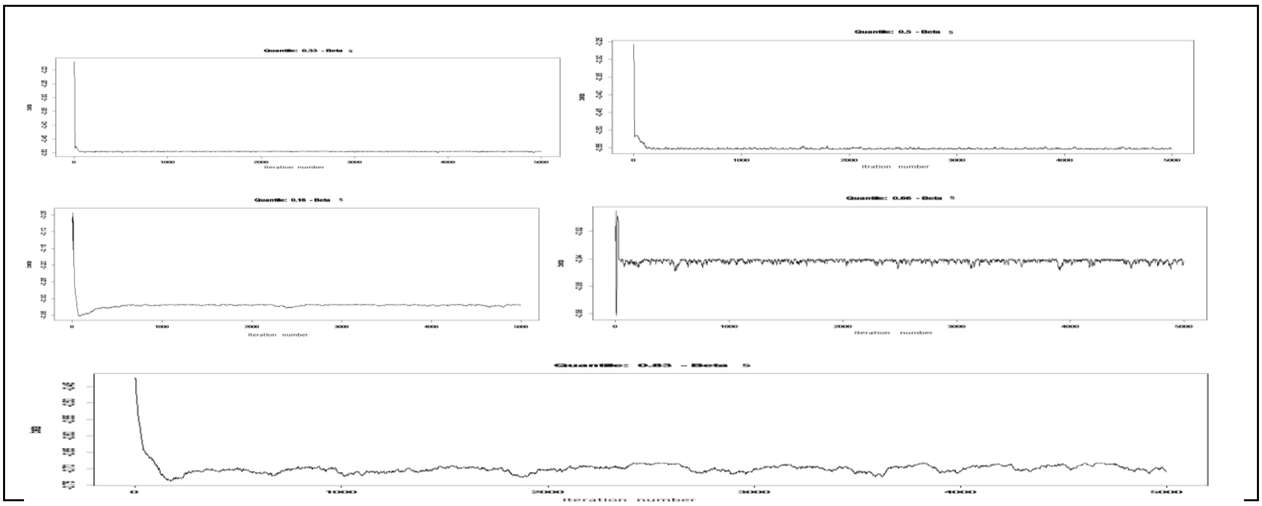

Figure 9: Plot for β_5 at five quantile and based on 5000 iterations.

Figure 9 show that the estimates of $[\beta_5]$ {average taxes imposed} for quantile regression model at the five quantile proportion were stationary through (5000) iterations. But the gap between upper bound and lower bound for estimated parameter $[\beta_5]$ {average taxes imposed.} was convergent (at credible intervals 95%) through (5000) iterations.

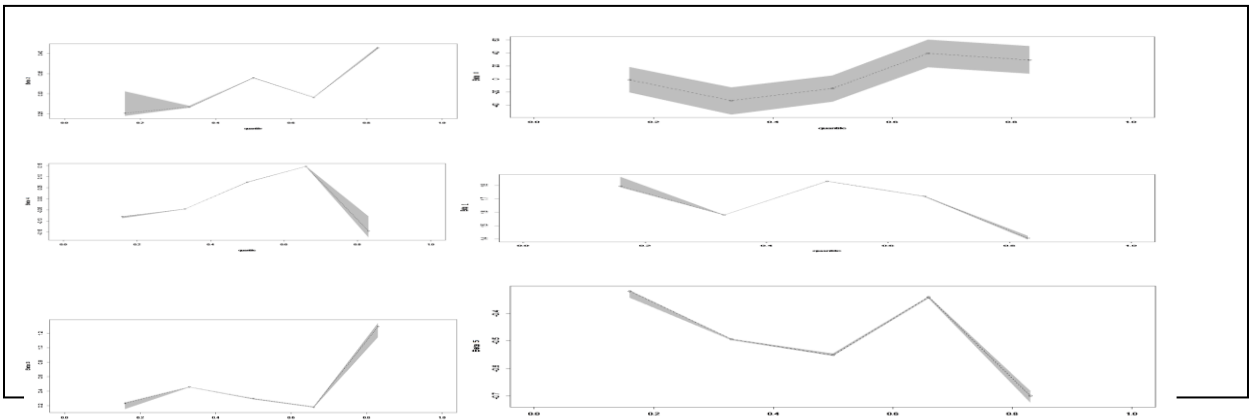

Figure 10: Estimate of the variables coefficients through five quantiles by Bayesian Lasso quantile regression

4. Conclusion

Through the results from the quantile regression the best model to represent the data of the phenomenon under study is quantile regression model at proportion (0.83) based on the value of the pseudo-R squared = 0.815514. This shows the strength of this model in explaining the variation in average number of poor Iraqi households through independent variables, comparing with the regression model at other quantile proportions. At proportion (0.83) there are three variables (Unemployment Average, average Monthly per capita income, average Spending monthly per capita on basic food) with significant effect on the average number of poor Iraqi households. Using Bayesian Lasso quantile regression method we also find that unemployment is the most important variable, while the variable “Rising prices of basic food goods” has a weak effect.

Based on two methods, we find that the variable “Unemployment Average” is the most important factor in explaining the variation in the average number of poor Iraqi households at each quantile proportion used in this paper.

Refrences

- Akaike, H. (1973). *Information theory and an extension of the maximum likelihood principle*. In: Petrov, B.N. and Caski, F. eds., Akademiai Kiado, Budapest, 1973, pp.267-281.
- Chernozhukov, V. and Hansen, C. (2008). Instrumental variable quantile regression: A robust inference approach. *Journal of Econometrics*, 142 (1), pp. 379-398.

- Hahn, J. (1995). Bootstrapping quantile regression estimators. *Econometric Theory* 11, pp. 105-121.
- Koenker, R. (2004). Quantile regression for longitudinal data. *Journal of Multivariate Analysis*, 91(1), pp. 74–89.
- Koenker, R. (2005). *Quantile Regression. Cambridge Books*. Cambridge University Press.
- Koenker, R. (2013). quantreg: Quantile regression. R package version 5.05.
- Koenker, R. and Bassett, G.J. (1978). Regression quantiles. *Econometrica*, 46, pp. 33-50.
- Koenker, R. and D'Orey, V. (1987). Algorithm AS 229: Computing regression quantiles. *Journal of the Royal Statistical Society*: Series C (Applied Statistics) 36, pp. 383-393.
- Koenker, R. and Machado, J. A. F. (1999). Goodness of fit and related inference processes for quantile regression. *Journal of the American Statistical Association*, 94, pp. 1296-1310.
- Kozumi, H. and Kobayashi, G. (2011). Gibbs sampling methods for Bayesian quantile regression. *Journal of Statistical Computation and Simulation*, 81, pp. 1565-1578.
- Qing, L., Xi, R. and Lin, N. (2010). Bayesian Regularized quantile Regression. *Journal Bayesian analysis*, 3, pp.1-24.
- Schwarz, G.E. (1978). Estimating the dimension of a model. *Annals of statistics*, 6 (2), pp. 461–464.